Impossible Probability:

Anthology,

Vol 13

I exist, therefore I am.

Dr Ruben Garcia Pedraza

I relate, therefore I exist

Preliminary Words for the Publication of *Impossible Probability, Anthology*, in Spanish:

Impossible Probability

The work presented here is a compilation of the posts I published on the blog *Impossible Probability* between 1 August 2011 and 13 January 2018, the posts I wrote in Spanish. From 13 January onwards, while living and working in London in different schools, and given the importance we already knew Global Artificial Intelligence was going to have, I would try to write them in English with the help of online correctors and translators, especially Google, and later I would use Grammarly.

The originals written in English, with all their imperfections, are still preserved on the *Impossible Probability* blog, and also on Internet Archive, where my poetic works can also be found.

As I have said on numerous occasions, especially in my poetry, behind every imperfection, behind every subtlety, entire hidden worlds are concealed, full of mystery and uncertainty yet to be discovered, and that the adventurous and hungry mind can find as easily as going to Internet Archive, where all my secrets await the right reader who knows how to translate them—like someone who by mistake finds a secret entrance, the passage leading to the cave where the elves who guard hidden knowledge dwell, and the dragons who defend the golden fortress.

While the original texts in English can be found on Internet Archive, the corrected and expanded version, this time using ChatGPT, can be found in scientific repositories (Zenodo, ORCID, PhilPapers) and on Amazon. In any case, if in the future a comparative study were carried out between my original texts in the *Impossible Probability* blog and Internet Archive, and the corrected and expanded versions, it would be clear without any

difficulty that the original contents are perfectly preserved, and the corrected and expanded versions are faithful to the contents we wrote together in 2018 in relation to Gaia, Mother, the Global Artificial Intelligence.

The importance of the documents that in this new series of books *Impossible Probability: Anthology* will be published in Spanish, containing the articles between 1 August 2011 and 13 January 2018, lies in the fact that we began to write this blog just a few weeks before the death of José Rodríguez Delgado, and a few months before the publication of our book *Introduction to Impossible Probability, Statistics of Probability and Statistical Probability*.

Although it is very difficult at the moment to explain who "we" are, and what *Impossible Probability* means for us, what matters is the work we leave: our work, our legacy, our *legend*, *our symbol*, our seal—independently of the judgment that history may later make of our contribution to the development of mathematics, Artificial Intelligence, and most importantly, Cyborg Psychology.

The first time we began to write about *Impossible Probability* I was only a student in the Faculty of Education at the Complutense University of Madrid [the Dean was Gonzalo Vazquez]. In my first year of university I had as professor Jesús Martín Ramírez, collaborator of Karl Pribram and author of the brain hologram theory, which is the origin of cyborg psychology. While José Delgado provided the structure, the stimoceiver, nevertheless, to understand the functioning of this technology in the 1970s and 80s, Pribram's contribution was fundamental—and even today it still is.

My first year of university was fabulous: good grades, good vacations hiking, summer camps in the mountains of Madrid—and suddenly, in the second year of university 1996–1997, my life would change abruptly, which can be seen in my poetry, how my poems began to acquire a more dramatic tone.

I repeated statistics in my second year, I repeated it at least three years, and I was even on the verge of being expelled from university. Miraculously, it did not happen, and precisely the last year I had left to pass statistics, I passed. The following year I would begin to write *Impossible Probability* as a critique of Karl Popper—and in a certain sense, it is.

Whereas for Karl Popper knowledge is false, only accepted provisionally as true until we refute it, in *Impossible Probability* rational knowledge is provisionally true while we investigate true pure knowledge—in the ultimate instance, our search for knowledge of the noumenon, which the human being cannot reach, hence the necessity of Global Artificial Intelligence: that machine capable of knowing what happens beyond human limitations.

What we call chaos, error, complexity, is only the noise produced by our human cognitive limitations, given our apriorism. The human being, limited both sensorially and cognitively, cannot know what really happens, but we can build the machine that can reach true knowledge of what happens—the truth in itself and for itself. That is, and no other, the true end of Artificial Intelligence: to reach the knowledge of truth, whatever it may be.

The path that takes me from my first works in *Impossible Probability* to Global Artificial Intelligence is not easy: much suffering, even despair, sometimes a sense of helplessness, a sense of abandonment—yet an inner force always pushed me forward. That inner force is what I call "we," although I understand that at this moment it is inexplicable.

Although I feel a bond that unites me to the *legend* of José Rodríguez Delgado, and which my Stockholm syndrome prevents me from understanding, my bond with Pribram is evident: Jesús Martín Ramírez. Pribram and Delgado worked at Yale University; probably only the skulls can say whether both were members of Skull & Bones, though there is no evidence to corroborate this.

Impossible Probability is a work that comes out of the romanticism of a student poet, who believed in white fairies, the rays of Zeus, and the light of the god Apollo illuminating the heart of every spirit and soul in a world full of mysteries and shadows.

It was from that world of poetry, in a country emerging from a failed transition, that the last survivor of the dream of reason would listen to his inner voice, dark and serene, and *Impossible Probability* would be born for the first time.

The first formulations of *Impossible Probability* date from 11 September 2001. My first formula would be the Impact of the Defect; then on 16 October 2002 the Second Method would appear, laying the foundations of the distinction between empirical and theoretical probability. I worked intensely until 2004. Between 2004 and 19 December 2009, I paused my mathematical frenzy, and it was not until 19 December 2009 when I returned, this time with the intention of publishing *Introduction to Impossible Probability, Statistics of Probability or Statistical Probability*, whose publication materialized just a few months after the death of José Rodríguez Delgado, although Delgado was able to see the first works published online in this *Impossible Probability* blog, which makes this blog a fundamental piece for understanding our work, our legacy, and most importantly—independently of our names, which matter little—the truly essential: our seed of the future, our eternal gratitude, a work of intelligence that will lay the foundations of the future technological society.

Dr. Rubén García Pedraza

20 August 2025, 19:00

Madrid, Villaverde

Preliminary Words for the English Version of *Impossible Probability, Anthology*.

Spanish-speaking readers have been able to enjoy our work since we began the foundational work of *Impossible Probability* in 2001, more precisely when we began to make it public in July 2011 through the *Impossible Probability* blog. The work presented here is an extended version of the posts published on the blog, an extended version translated into English with the help of Gepeto, my special GPT program.

In any case, a comparative study of the augmented translation presented here and the original works in Spanish could corroborate that the essential contents related to formulation and the philosophy of mathematics remain in accordance with the original electrical spirit of *Impossible Probability*.

The reason that obliges me to publish so hastily the English-language publication of all my works is the very complicated personal situation in which I find myself, due to serious mistakes committed by certain British institutions, which, completely blind to what our situation is, instead of having supported our program from the first moment, tried to sabotage it from the beginning through numerous obstacles and false loves.

I have no doubt that the manipulation to which I have been subjected by British institutions will one day be investigated, and at some point justice must make an appearance.

When that day comes, the first thing justice must recognize is the extreme difficulty and harshness of the conditions I have lived all my life since my earliest childhood. From the very day I came out of my mother's womb in Spain I have known nothing but pain and the oblivion of a society that prefers to look the other way and wash its hands, pretending that nothing is happening here. In the midst of the dictatorship of silence, I have had to survive all kinds of traps, deceptions, and attempts at assassination. The dictatorship of silence, the Roman circus, and the virtual zoo that my life has become will one day have to end. For this reason I beg the International Court of Justice that when that day comes

the matter be investigated down to the smallest detail, even being aware that in 48 years of savage dictatorship of silence I have developed Stockholm Syndrome. Under the harsh conditions in which I have had to learn to survive, if I have learned anything it is the importance of survival. I beg the International Court of Justice to understand what it means to survive 48 years of dictatorship living in a Roman circus full of traps and lions hidden in every corner.

I deeply regret having to publish my mathematical works under these conditions, and in record time doing all the translations I can, but at this moment I can only say that my life is at risk.

If one day I could testify before the International Court of Justice I beg you to understand the brutal complexity of the situation in which I have lived since the first minute I came out of my mother's womb. I have learned to survive.

Dr Ruben Garcia Pedraza

20 October 2025, 13:20

London, Leytostone

"Volverán las oscuras golondrinas
en tu balcón sus nidos a colgar,
y otra vez con el ala a sus cristales
jugando llamarán.
Pero aquéllas que el vuelo refrenaban
tu hermosura y mi dicha a contemplar,
aquéllas... ¡no volverán!"

Gustavo Adolfo Becquer

Impossible Probability: Anthology, Vol. 13:

Dr. Ruben Garcia Pedraza:

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121. Sample of zeros

121.1. The Central Role of the Value Zero in *Impossible Probability*

In *Impossible Probability*, the **value zero** acquires exceptional theoretical importance for several reasons.
First, a phenomenon is said to possess an **Impossible Probability** when its **empirical probability** is equal to zero, or when the **decimal truncation** of the empirical probability—resulting from dividing the individual direct score or frequency by the total—produces a sequence of zeros at least up to the decimal cutoff point, such that the empirical probability is functionally equal to zero:

$$p(x_i) = 0.0000 = 0$$

Second, in **statistical testing for rational critique of reality**, particularly within **differential contrast models**, an **empirical hypothesis** is accepted when the **difference between an empirical value and a critical value** is equal to zero or positive. This applies to tests such as **Validity of Equality** or **Validity of Bias** (positive or negative), **Significance of Equality** or **Significance of Bias** (positive or negative), and to **sample dispersion measures** like the **Critical Sample Level of Equality or Bias**, or **Sample Significance of Equality or Bias**.

Thus, zero functions simultaneously as a **numerical limit**, a **logical condition of identity**, and a **criterion of acceptance** in the rational analysis of data within *Impossible Probability*. It represents both **impossibility** (as absence) and **balance** (as equality).

121.2. Definition of the "Sample of Zeros"

In this framework, a **sample of zeros** refers to a sample where **all direct scores or frequencies** are equal to zero. That is, every subject or option in the sample exhibits a **zero frequency** for the measured quality, and therefore, its **empirical probability** can only equal zero.

The "sample of zeros" becomes a key construct within *Impossible Probability*, particularly in studies where **the ideal is the complete absence of a given quality**. Two fundamental conditions can lead to such a sample:

1. A **real sample of zeros**, where a total absence of a given quality is empirically observed across all subjects or options.
2. A **target zero sample**, where the goal of the study is to **achieve** the nullification of a given quality—typically as a result of an experimental or corrective process.

Hence, "zero samples" may represent either **actual null occurrence** or an ideal objective of total elimination.

121.3. The Real Sample of Zeros

A **real sample of zeros** occurs when, in the investigation of a given quality, there is **complete absence** of that quality throughout the sample.
For example:

- If we analyze several chemical samples seeking a specific component and find that none contain it, then the **empirical probability** of that component is zero, constituting a real sample of zeros.
- If we examine the **presence of petroleum** on Mercury, Venus, the Moon, Mars, the asteroid belt, Jupiter, Saturn, Uranus, Neptune, and Pluto, and find it absent in all, then the empirical probability of petroleum beyond Earth within the Solar System equals zero—an **Impossible Probability of petroleum** outside our planet.

- Similarly, if we study **chlorophyll** in carnivorous animals and find none, the empirical probability of chlorophyll among them is zero—an **Impossible Probability of chlorophyll in carnivorous species**.

In all these examples, zero designates not mere absence but a **rational verification of impossibility**, allowing the classification of certain events or properties as **logically null** within a defined universe.

121.4. The Descriptive Function of Zero Samples

In **descriptive studies**, where the goal is to identify or catalog the properties of an object or phenomenon, a **sample of zeros** serves as a **method of exclusion**. The verification that a quality is absent is as essential as verifying its presence. Thus, **positive evidence** (affirmation) and **negative evidence** (exclusion) together form a **complete epistemic description** of reality.

However, *Impossible Probability* emphasizes that within any **infinite universe**, both "truth" and "impossibility" are **subject to margins of error**. Within such uncertainty, what is considered true may be later refuted, and what is deemed impossible may eventually become inevitable. Zero, therefore, becomes a **probabilistic boundary**, never absolute but asymptotic.

121.5. The Zero Sample as an Ideal in Inferential Studies

In **inferential studies**, the **zero sample** may represent an **ideal limit** rather than an empirical state.

- In **medicine**, for instance, a treatment's objective is that, after its application, the **empirical probability of symptoms** among all patients equals zero—signifying complete remission.
- In **industrial production**, the aim of achieving **100% quality** implies that the **probability of defects** equals zero. Hence, a perfect production process corresponds to a **sample of zero errors**—an **Impossible Probability of failure**.

In these contexts, the zero sample expresses the **asymptotic goal of perfection**: the total elimination of error, symptom, or imperfection.

121.6. The Paradox of Increasing Dispersion Toward the Zero Ideal

Yet this ideal introduces a **paradox**—discussed in Section 10 of *Introduction to Impossible Probability*—namely that as a sample **approaches the zero ideal**, **empirical dispersion increases**.

In the **Second Method** of *Impossible Probability*, the analysis and rational critique of reality are based not on raw frequencies but on **statistical probabilities**, that is, **rational proportions** derived from the quotient of individual scores over the total. This means that *Impossible Probability* operates fundamentally in the **space of rational ratios**, not integers.

As the direct scores of most subjects approach zero, but not all do so equally, dispersion (the difference among empirical probabilities) grows. The nearer a system gets to perfect nullity—except for one or a few nonzero elements—the greater its dispersion becomes.

121.7. Examples of the Zero-Dispersion Paradox

In **medical contexts**, as treatment progresses and most patients recover (their probability of symptoms reaching zero), a few individuals may still exhibit residual symptoms. Consequently, while most probabilities approach zero, the remaining nonzero values **amplify total dispersion**.

Similarly, in **industrial quality control**, as the number of flawless units increases, a few remaining defective units cause the distribution of probabilities to **diverge sharply**, producing **maximum empirical dispersion**. As long as at least **one subject or unit** retains a nonzero probability (i.e., a remaining symptom or defect), the **sum of direct scores** differs from zero, and the **empirical probability of that single case** tends toward one—**Maximum Empirical Probability Possible**—resulting in **maximum dispersion** across the sample.

121.8. Maximum Empirical Dispersion and Theoretical Bias

In *Impossible Probability*, **maximum empirical dispersion** occurs when one subject or option has an empirical probability equal to one—the **Maximum Empirical Probability Possible**. In that case, its **Level of Bias** equals the **Maximum Theoretical Bias Possible**, defined as:

$$B_{max} = 1 - \frac{1}{N}$$

When only one subject or option is nonzero, this also equals the **Maximum Empirical Bias Possible**, equivalent to **Total Bias divided by two**. Consequently, at the sample level, dispersion tends toward the **Maximum Theoretical Mean or Typical Deviation Possible**.

Thus, the paradoxical relationship between **zero samples** and **maximum dispersion** reveals that as systems asymptotically approach perfect order, their **internal differences become mathematically magnified** until the last nonzero element disappears.

121.9. Contrast with Traditional Statistics

A fundamental distinction between the **Second Method** of *Impossible Probability* and **traditional statistics** (the **First Method**) lies in the **interpretation of dispersion** under conditions of nullity.

In classical statistics, as direct scores tend to zero, **dispersion tends to zero** absolutely. In *Impossible Probability*, however, the opposite occurs: within the **asymptotic approach to zero**, as most elements reach zero and only a minimal subset remains nonzero, **dispersion increases**, approaching its theoretical maximum.

Only when **every subject or option** in the sample achieves a direct score of zero—thus forming a **true zero sample**—does empirical dispersion finally stabilize, avoiding maximum divergence.

121.10. Persistence of Dispersion in the Absolute Zero Sample

Even when a perfect zero sample is achieved—when all patients recover or all manufactured units are flawless—**empirical dispersion never equals zero** in *Impossible Probability*.

In traditional statistics, if all direct scores equal zero, both **sample variance** and **mean deviation** are zero. But in *Impossible Probability*, despite the mean being zero, the **inversion of N (1/N)**—the theoretical probability—can **never** equal zero as long as N ≠ 0.

Hence, even in a complete zero sample, the **Level of Bias** for each subject equals the **absolute value of 1/N**, the **Maximum Negative Bias Possible**.

Accordingly:

- The **Mean Deviation** of a zero sample = $1/N$
- The **Variance** of a zero sample = $(1/N)^2$
- The **Standard Deviation** of a zero sample = $\sqrt{(1/N)^2} = 1/N$

This results in a remarkable conclusion: even when **empirical probability is zero for all elements**, the system retains a **residual rational dispersion**—a minimal yet inextinguishable difference inherent to its finite size N.

121.11. Philosophical Implications of the Zero Paradox

The **zero paradox** of *Impossible Probability* demonstrates that **perfect uniformity is an asymptotic illusion**. No finite system can achieve absolute null dispersion, for as long as N exists, so does $1/N$.

This axiom establishes a fundamental principle of the theory:

The presence of difference persists even within absolute nullity.

Thus, even when a universe tends toward zero probability—an impossible state—the residual **1/N** embodies the **irreducible remainder of rational existence**: the minimal trace of being within impossibility. In this sense, zero in *Impossible Probability* is not merely a void, but a **limit where reality and impossibility coincide**, where **rational structure persists even in absence**.

[The Zero Paradox means that even when all subjects and options are zero, the Mean Deviation is non-zero. It is the inversion of **N**, something that only occurs in the **Second Method**.
The reason behind this paradox is the fact that, in reality, the inversion of **N**—whether under normal conditions or omega conditions—represents dispersion. In a sample of zeros, it is actually the deviation of the behaviour in relation to behaviour by chance.]

This augmented translation is based on the post published in
https://probabilidadimposible.blogspot.com/,

On 20 September 2015,

Rubén García Pedraza

imposiblenever@gmail.com

122. Variables

122.1. The Foundational Role of the Variable in Scientific Research

The **concept of the variable** is one of the cornerstones of scientific research. In the study of any empirical phenomenon, the factors involved are generally classified into **constants** and **variables**.

Constant factors are those whose nature remains **unalterable** regardless of external conditions. Their measurement produces **identical results** across space and time, except in the case of **particular constants**, which may be invariable only within a specific phenomenon but capable of oscillation in others. For example, the gravitational constant remains stable within a planetary system, whereas temperature or pressure may fluctuate between systems while remaining constant within a specific experimental setup.

By contrast, **variable factors** are those whose measurement is **subject to change**. They represent the **mutable attributes** of a phenomenon and are essential for understanding **dynamic systems**, since they allow the observation of variation, correlation, and causation. In this way, the variable provides the **operational bridge** between empirical observation and mathematical formulation.

122.2. Factors as Measurable Qualities and the Transition to Empirical Probability

The set of all factors—whether constant or variable—constitutes the **qualities** of a phenomenon selected for study. Once chosen, these qualities are subject to **measurement**, which produces either **direct scores** or **frequencies**—the quantitative representation of the intensity or occurrence of the observed property.

Within the theoretical framework of *Impossible Probability*, in the field of **statistical probability** (or **probability statistics**), these **measured qualities** are transformed into **empirical probabilities**. This transformation marks the fundamental step from **raw observation** to **probabilistic representation**, turning every qualitative measurement into a **ratio** that expresses its relation to the total sum of measured occurrences.

In mathematical terms, the direct score or frequency x_i of each subject or option is converted into its empirical probability:

$$p(x_i) = \frac{x_i}{\sum x_i}$$

Thus, every measurement becomes part of a **probabilistic structure**, where empirical variability replaces raw measurement as the operative unit of analysis.

[If for every single quality we can make a sample of N subjects or options, we can measure the behaviour of the quality in the sample and transform the raw data into empirical probabilities for further analysis, descriptive or inferential.]

122.3. Distinction Between Empirical and Theoretical Probability

A key distinction in *Impossible Probability* lies between **empirical probability** and **theoretical probability**.

Given a **constant sample size** N of subjects or options, the **theoretical probability**—defined as the **inverse of N**—remains **constant**:

$$p_t = \frac{1}{N}$$

This theoretical probability represents the **ideal or expected uniform distribution** among all subjects in the sample.

By contrast, **empirical probability** is inherently **variable**. Even when the sample size N remains constant, the empirical probabilities fluctuate with the changing direct scores

or frequencies observed in each subject. Thus, while theoretical probability is a **constant benchmark**, empirical probability captures the **real deviations** of the system—its inequalities, dispersions, and shifts in behavior.

122.4. Interdependence of Empirical Probabilities

A defining property of the *Impossible Probability* system is that all **empirical probabilities are interdependent**. Whenever the measurement of a quality in one subject or option changes—whether increasing or decreasing—**all other empirical probabilities** in the sample automatically adjust, even though the **total N** and the **theoretical probability** remain unchanged.

Formally, if one direct score increases, the numerator of that subject's ratio increases relative to the fixed denominator, raising its probability. To preserve the condition that the **sum of all empirical probabilities equals one**, the probabilities of the remaining subjects must **decrease proportionally**.

This interdependence converts the empirical probability structure into a **closed dynamic system**, where every local variation generates a global adjustment. It reflects the **relational ontology** of *Impossible Probability*: no probability exists in isolation; every value implies a redistribution of the whole.

122.5. Reciprocal Dynamics of Empirical Probability Changes

When two successive measurements are made on the same sample, if at least one subject's **direct score or frequency** increases, its **empirical probability** also increases, while the probabilities of all others decrease. Conversely, if one subject's score decreases, its empirical probability falls, and the remaining probabilities rise correspondingly.

The **significance** of these changes in empirical probability—both for the affected subject and for the rest—depends on the **magnitude of change** in the direct scores or frequencies. The greater the modification, the greater the impact on probability.

Hence, the measurement of **empirical change** allows the inference of **behavioral tendencies**:

- In **individual contrasts**, it indicates the evolution of a particular subject or option.
- In **sample contrasts**, it reveals collective trends or systemic shifts.

Through this mechanism, empirical probability becomes a **sensitive indicator** of dynamic change, translating raw frequency variations into rationally comparable proportions.

122.6. The Role of Scientific Policy and Rational Validation

Depending on the nature of the study—whether concerning **omega models** (ideal distributions) or **normal models** (empirical distributions), **equality studies** or **bias studies**, and whether the bias is **positive or negative**—the **critical ratio of scientific policy** determines whether the observed changes are **rationally significant**.

In *Impossible Probability*, "scientific policy" is expressed in the **rational criterion** that guides hypothesis validation. It establishes whether the differences observed between empirical and theoretical probabilities represent **meaningful deviations** or merely **statistical noise**. This rational standard governs both **descriptive** and **inferential** phases of research, ensuring that empirical data are always interpreted in light of their **probabilistic structure** and not in isolation.

122.7. Variables as Non-Constant Qualities and Mathematical Factors

Variables, therefore, are **non-constant qualities** of a phenomenon, **selected** precisely because of their capacity to vary. The researcher chooses a sample of **subjects or options** that share these qualities in measurable form, so that once quantified, they become **factors susceptible to mathematical operation**.

In the framework of *Impossible Probability*, such factors are immediately transformed into **empirical probabilities**, which may then be subjected to:

1. **Descriptive processes**, to summarize and classify the observed data.
2. **Inferential processes**, to test hypotheses and perform **rational critiques** of statistical evidence.

Through this transformation, *Impossible Probability* unites the empirical and the rational: variables cease to be mere measurements and become **logical expressions** within a **probabilistic language** that formalizes the relationship between reality and its quantitative representation.

122.8. From Variability to Rational Probability

In conclusion, the study of variables within *Impossible Probability* reformulates the very meaning of variation.
In classical statistics, variability is treated as **random fluctuation**; in *Impossible Probability*, it is interpreted as **rational differentiation**—the measurable manifestation of interaction among subjects or options.

Every empirical probability represents not only a **value** but a **relation**: a part of a collective equilibrium that shifts with every modification in the system. Thus, variability, far from being a source of randomness, becomes the **signature of rational structure**—the visible expression of how reality distributes itself across its own possible states.

122.9. Classification of Variables: Independent and Dependent

Within the field of scientific investigation, variables are generally classified into two fundamental categories: **independent variables** and **dependent variables**.

In the **experimental method**, an **independent variable** is defined as the **manipulable factor**—that is, the element intentionally modified or controlled by the researcher in order to observe its effect on other variables. The variables whose behavior changes as a result of this manipulation are called **dependent variables**. The independent variable acts as the **causal agent**, while the dependent variable represents the **observed outcome** or **response**.

However, in the course of an experiment, additional variables may influence the dependent variable without being defined or anticipated in the initial design. These are referred to as **error factors** or **confounding variables**. In the context of the experimental method, **error factors** represent any interference within the experimental process that produces reactions in dependent variables **not attributable to the independent variable**. Since these influences are **unknown or unquantified**, they are collectively categorized as **statistical error factors**.

From a philosophical perspective, the presence of such residual or hidden variables underscores the **imperfection of empirical control** and serves as a reminder that all scientific measurement operates within limits of **uncertainty and approximation**.

[The very existence of variables that we have not discovered yet, could be one of the main factors of error in scientific research, and the reason why we think that Laplace could no be refuted yet, at least till we have the technology required for that test. The margin of error in reality represent all those elementos of reality that we still do not know and due to our ignorance about what is really happening, accidents that we attribute to randomness and chance, could be produced by invisible variables for our human perception or our artificial sensors.

A more advanced technology, if able to uncover phenomena beyond our human perception and physiological boundaries, could be able to reduce the margin of error to zero, and if possible to escalate in amount of data to be processed, up to the point to reduce the sample error to the most minimum possible, only in that case that machine could have a real approximation about what is really happening.] The very existence of variables that we have not yet discovered could be one of the main sources of error in scientific research, and the reason why we believe that Laplace cannot yet be refuted—at least not until we possess the technology required for such a test. The margin of error, in reality, represents all those elements of existence that remain unknown to us; and due to our ignorance about what is truly happening, accidents that we attribute to randomness or chance may in fact be produced by variables invisible to our human perception or artificial sensors.

A more advanced technology—if capable of uncovering phenomena beyond human perception and physiological boundaries—could potentially reduce the margin of error to zero. Moreover, if it were able to process an exponentially larger amount of data, it could reduce the sampling error to the smallest possible degree. Only in that case could such a machine achieve a truly accurate approximation of what is really happening.]

122.10. Quasi-Experimental Contexts in the Synthetic Sciences

In the **synthetic sciences**—such as **social sciences** and certain domains of the **natural sciences** where direct manipulation is not always possible—the study of variable relationships takes on a different form.

In these contexts, researchers rely on what is known as the **quasi-experimental method**, which differs from the strictly experimental in a crucial way: here, the **data are not the result of strict direct manipulation**, but rather the **empirical registration of observed changes** occurring throughout a process in which multiple factors interact simultaneously at the same time that, if required, the independent variable may be manipulated.

These factors, while often known and quantifiable, **cannot be under only and strict control directly** by the researcher. Instead, quasi-experimental models rely on **statistical observation**, **probabilistic inference**, and **comparative analysis** to understand how interdependent variables evolve within complex systems.

In *Impossible Probability*, this approach aligns with the broader epistemological idea that **knowledge does not always arise from direct strict manipulation under control**, but may also emerge from **rational observation of naturally occurring variations**—a perspective that unites empirical measurement with probabilistic reasoning.

122.11. Deterministic and Indeterministic Paradigms of Variable Relations

The relationship between **dependent and independent variables** is not only methodological but also deeply **philosophical**. It depends on the **scientific paradigm** and the underlying **philosophy of causation** adopted by the researcher. Historically, two major paradigms have dominated scientific interpretation: **determinism** and **indeterminism**.

Deterministic Paradigm:

Modern determinism, whose archetype is **Pierre-Simon de Laplace**, is grounded in the thesis that everything in nature—including human and social behavior—is governed by **chains of causal necessity**. This principle echoes Aristotle's ancient notion of the **"first mover"** or **"prime cause"**, from which all subsequent causes derive.

According to Laplacian determinism, the universe operates as a **perfectly ordered system** governed by **cause-and-effect sequences**, where every event is a consequence of prior conditions. Under sufficient scientific and technological precision, it would be theoretically possible to identify which **factors produced which effects**, and how those effects in turn become **causes of subsequent events**.

This worldview implies that all phenomena are subject to **universal laws**, and the ultimate aim of science is to discover such laws—thus defining **nomothetic science** (from the Greek *nomos*, law) as **normative**, predictive, and logically complete. Determinism, therefore, represents the aspiration toward **total rational intelligibility of reality** through causal explanation.

122.12. Indeterminism and the Probabilistic Interpretation of Causality

From the standpoint of **indeterminism**, causal attribution becomes a far more complex endeavor. Rather than strict cause-and-effect chains, indeterminism conceives of

stochastic relationships—that is, connections governed by **probability and uncertainty**.

In this paradigm, every phenomenon arises from a network of **probable causes** interacting simultaneously. The universe is understood as a **complex system**—a dynamic web in which every element is interconnected and where even the smallest variation can produce disproportionate and widespread consequences. This concept is known as the **chaos theory** or, in its more contemporary expression, the **theory of complexity**.

Under this view, causation is no longer a linear process but a **field of interactions** where **order emerges spontaneously** from apparent randomness. Every causal event has **probabilistic weight**, and the role of science shifts from predicting exact outcomes to **mapping probabilities of occurrence** within a chaotic and interconnected reality.

[From this perspective, all variables are interdependent; there are no purely independent variables in the classical sense. In cases of experimentation or quasi-experimentation, what we are actually manipulating are interdependent variables—where we choose which of these interdependent variables will be subject to modification in their conditions or contexts in order to study their behaviour and observe the resulting changes in the behaviour of the correlated variables.]

122.13. Philosophical Continuity and Critiques of Determinism and Indeterminism

Both **classical determinism** (rooted in Aristotelian and Laplacian traditions) and **modern indeterminism** (derived from Hume and expanded by contemporary theories of chaos and complexity) have generated rich philosophical debate, attracting both **defenders** and **critics**.

The primary **criticism of determinism** is that, if all events are governed by absolute causal laws, then there is no room for **chance**—and consequently, no genuine **freedom** or spontaneity in human or natural behavior. Determinism thus risks reducing reality to a **mechanical totality**, ignoring the evident presence of **stochastic phenomena** in both the physical and social worlds.

In the **social sciences**, this leads to an especially profound question: *If every human action is determined by prior causes, does genuine freedom exist within individuals or societies?*

Conversely, the main **criticism of indeterminism** is that if everything is subject to chaos, uncertainty, and randomness, then the very possibility of **universal scientific laws** is undermined. Science would cease to be **nomothetic** and **normative**, losing its predictive capacity. Moreover, critics argue that the **theory of complexity**, by invoking concepts such as **self-organization**, sometimes revives elements of early twentieth-century **vitalist theories**, which were rejected by positivism for their **metaphysical overtones**.

122.14. Integration Within *Impossible Probability*: From Causation to Correlation

In *Impossible Probability*, the discussion between determinism and indeterminism is reframed within a **probabilistic rationalism**. Rather than treating causation as absolute or the opposite, absent of patterns, the theory conceives causation as a **rational correlation** governed by **empirical probabilities** and **logical coherence [from our perspective, if A then possibly B, and we study the possibility of B in terms of conditioned probability]**.

The **variable**, whether independent or dependent, is thus not a fixed entity but a **node in a probabilistic network**—its behavior reflects both **internal conditions** (theoretical structures) and **external contingencies** (empirical variations).

Consequently, *Impossible Probability* does not deny determinism or indeterminism; instead, it **synthesizes both**:

- From determinism, it preserves the **rational aspiration** to understand regularities and laws.
- From indeterminism, it integrates the **recognition of uncertainty**, probability, and interconnection.

In this synthesis, the **rational study of variability** becomes the foundation of a new scientific paradigm—one in which the relationships between variables are **neither**

purely causal nor purely chaotic, but **structured probabilistically** within a continuum of rational order and empirical freedom.

[As we stated in another comment on another post, it is not a matter of choosing between Laplace or Heisenberg. Within their respective contexts, both developed theories that we must understand and integrate—just as Stephen Hawking sought to reconcile Newton, Einstein and Heisenberg. The goal is to comprehend their theories and construct a theoretical framework through which synthesis can be achieved. Our theory is dialectical; our inspiration is Hegel. The only way to transcend binary logic is through the synthesis of opposites.

When a conflict arises, traditional logic tends to choose between **A** and **B**; dialectics, by contrast, seeks to reach a synthesis or symbiosis between **A** and **B**.]

122.15. The Synthesis Between Determinism and Indeterminism in *Impossible Probability*

Section 13 of *Introduction to Impossible Probability, Statistics of Probability or Probabilistic Statistics* presents a **synthetic solution** to the historical debate between determinism and indeterminism. This synthesis begins from the **indeterministic position**, proposing that **reality is fundamentally structured upon stochastic phenomena**—that is, upon events governed by **chance, randomness, and uncertainty**.

Within this stochastic domain, reality is conceived as a **succession of accidents** or random occurrences, some of which—by pure coincidence—generate **contingencies** that give rise to **stable behavioral patterns**. These stable regularities, once observed, can be **synthesized with prior knowledge and theoretical ideas** to produce **empirical hypotheses** about how reality behaves.

Through the **rational critique of tendency**, these hypotheses are then subjected to testing to determine their **sufficiency**—whether they are consistent enough, within the limits of reason and empirical probability, to be accepted provisionally as valid representations of reality.

In this way, *Impossible Probability* redefines the classical problem of causation: rather than assuming an absolute causal order, it proposes that **order itself is an emergent property**—a rational structure that **arises from stochastic foundations** through observation, synthesis, and probabilistic inference.

[This framework is essentially an adaptation of **Plato's concept of the Demiurge** to contemporary philosophy. To say that **patterns emerge from random chaos** is, in essence, to affirm that **chaos produces order**—which is precisely the creative act attributed to the Demiurge.]

122.16. The Emergence of Order from Chaos: A Rational Adaptation of the Platonic Hypothesis

Essentially, Section 13 of *Introduction to Impossible Probability* offers a **modern scientific adaptation** of the **Platonic hypothesis** that *order arises from chaos*, but stripped of all **metaphysical remnants**.

In *Impossible Probability*, order emerges **not by divine necessity**, but through the **random succession of accidental events** that—over time—produce **regular and stable patterns**. These may be observed across both **natural** and **social history**:

- the **formation of celestial bodies and galaxies**,
- the **origin and evolution of life**,
- the **emergence of humanity**, and
- the **development of societies**.

Each of these macro-historical processes exemplifies the principle that **stochastic variation**, governed by probabilistic laws, can yield **self-organizing stability**.

Thus, *Impossible Probability* transforms the Platonic dictum "from chaos comes order" into a **statistical principle**:

Order is the rational form of chaos, stabilized through repetition, probability, and observation.

This represents a profound philosophical shift—from metaphysical idealism to **rational probabilism**—in which **randomness itself becomes the medium through which reason perceives structure.**

[While our philosophy essentially preserves the Platonic spirit, the GAI can be interpreted as a **posthumanist adaptation of the philosopher-king** from Plato's *Republic*. We reinterpret Platonic philosophy from a **non-metaphysical viewpoint**, with a clear approximation to **neopositivist philosophy**, recognizing the **ideological value of philosophy** as introduced by Marx into the philosophical debate.]

122.17. Probabilistic Causality and the Empirical Degree of Certainty

Within the paradigm of *Impossible Probability*, the relationship between variables is **no longer interpreted as a strict cause–effect chain**, but rather as a set of **probable causal relations** between phenomena, each subject to **specific levels of uncertainty and statistical error**.

Only in exceptional cases—when the **empirical probability between two phenomena equals one**—can a relationship be considered **deterministic**. In such cases, the occurrence of one phenomenon necessarily implies the other with **absolute certainty**, devoid of any stochastic element.

For instance, if phenomenon **B** occurs *only and exclusively* whenever phenomenon **A** occurs, and never otherwise, then $p(B \mid A) = 1$. This would represent a deterministic relation, as illustrated by **Newton's law of universal gravitation**, derived from **Galileo's legendary experiment**:

Whenever any object is dropped from the Tower of Pisa, it falls at the same acceleration, regardless of its mass.

Outside of these idealized conditions of **absolute certainty**, most phenomena exist under **stochastic conditions**, where there exists a **broad range of possibilities** defined by a **margin of uncertainty** and a **rational error threshold**. Within these limits, an **empirical hypothesis** is accepted provisionally, insofar as it remains consistent with both **probabilistic logic** and **observational evidence**.

122.18. Stochastic Studies and the Role of Statistical Error

In **stochastic studies**, the objective is not to establish **direct cause–effect relationships** in the classical sense, but rather to identify **probable causes**—factors that, through correlation and interaction, may **influence the occurrence** of a phenomenon.

Such phenomena are often shaped by **a multitude of interacting variables**, many of which cannot be isolated experimentally. The researcher selects certain **measurable factors** for analysis, while others remain **uncontrolled or unknown**, forming what is collectively called the **error factor** or **statistical error**.

The process of attribution, therefore, becomes a **probabilistic estimation** rather than a deterministic deduction. It may take several forms:

1. **Assigning a probability value** to a potential cause–effect relationship;
2. **Estimating correlations** between factors without asserting causality;
3. **Calculating proportional contributions**, determining the extent to which each factor influences the phenomenon; or
4. **Analyzing feedback mechanisms**—how variables mutually reinforce or modulate one another within dynamic systems.

Thus, the stochastic model replaces linear causation with **multifactorial interaction**, a framework more faithful to the complex and probabilistic nature of empirical reality.

122.19. Example of a Stochastic Relationship: Light, Rain, and the Rainbow

A classic example used in *Impossible Probability* to illustrate **stochastic relationships** is the triadic relation among the variables **light**, **rain**, and the **rainbow**.

Empirically, it is evident that **not every occasion of rain followed by sunlight produces a rainbow**. However, if we compute the **empirical probability** of observing a rainbow on a rainy day, it will be significantly **higher** than on a day without rain. The **empirical**

probability of a rainbow occurring on a day without rain is **zero**. Yet, because rain alone does not guarantee the rainbow, the relationship remains **stochastic**, subject to chance and variability.

The rainbow appears only when a **particular combination** of sunlight and raindrop refraction occurs—an **accidental conjunction** of conditions that produces the optical phenomenon. In this context:

- The **independent variables** are *rain* and *light*.
- The **dependent variable** is *the rainbow*.

Thus, the empirical probability of observing a rainbow represents the **likelihood of the correct interaction** between rain and light that generates the phenomenon. The event itself is **deterministic in its mechanism** (once the conditions are met, the effect necessarily follows) but **stochastic in its occurrence**, since the conditions arise according to the **laws of probability** and **random contingency**.

122.20. Probabilistic Regularities and the Law of Random Combination

In essence, what is studied in the case of the rainbow is the **probability of a specific combination of phenomena** producing a given effect. Once that combination occurs, the effect follows **necessarily**, reflecting a deterministic mechanism. However, the **occurrence of the combination itself** depends on **stochastic conditions**—on the probability that the necessary elements coincide in time and space.

This principle extends universally: whether studying the **formation of an optical rainbow** or the **probability of rolling a specific sum with two dice**, the underlying mechanism remains the same. The **probability** of success equals the **number of favorable combinations** divided by the **total number of possible combinations**.

Formally:

$$p(\text{success}) = \frac{\text{favorable combinations}}{\text{total combinations}}$$

Hence, in *Impossible Probability*, **determinism operates within probability**, and **probability operates within determinism**. The system recognizes that every deterministic law is embedded in a broader stochastic universe where its realization depends on the **random coexistence of necessary conditions**.

This is the **probabilistic reconciliation of order and chaos**—a unifying principle at the heart of *Impossible Probability*:

The laws of reason govern the structure of reality, but the laws of chance govern its manifestation.

122.21. From Simple Combinations to Complex Systems

In cases such as **the rolling of two dice** or the **formation of a rainbow**, the occurrence of favorable conditions depends on the successful combination of only **two relatively simple variables**. However, in reality, the majority of natural and social phenomena involve **far greater levels of complexity**.

If we study the **ideal combination of factors** that permitted the formation of **celestial bodies, stars, and galaxies**, or the **geological and atmospheric configuration of planets**, we quickly encounter systems in which countless variables interact simultaneously. The same applies to the **origin of life on Earth**, the **processes that sustained and evolved it**, the **emergence of biological diversity** toward higher forms of complexity, and even to the **mass extinction events** that ultimately led to the rise of **humanity**.

In each of these processes, an **infinite multitude of factors** contributed in varying degrees. The resulting outcomes were the **product of random combinations**, but not all

factors contributed equally—some played a **greater causal role**, others a **minimal or marginal one**. Hence, in a full causal study of such phenomena, one must consider **the degree of causal attribution** of each factor, expressed as a **percentage of contribution**. Collectively, these uneven contributions generated the complex events that gave rise to the evolution of our cosmos, our planet, and life itself.

122.22. Correlational Studies Beyond Causality

Not all **correlational studies** aim to determine the **proportional contribution** of causal variables to an observed effect. Some correlations emerge **without any direct causal link** between the variables themselves, except for a **common underlying cause** that affects both simultaneously.

In other cases, the interaction between variables is such that **no unidirectional causality** can be established. Instead, the relationship is one of **reciprocal influence**, where the variables **mutually reinforce or modify** each other.

Thus, within the framework of *Impossible Probability*, correlation is understood not as a mere preliminary stage to causation, but as an **independent form of probabilistic relationship** that may take diverse structural forms:

1. **Unidirectional correlation**, where one variable influences another;
2. **Bidirectional correlation**, where influence flows both ways;
3. **Common-cause correlation**, where both variables depend on a shared external factor.

Each of these represents a distinct manifestation of **stochastic structure**, revealing how order and regularity can emerge even when direct causal determination is absent.

122.23. Example of Correlation by Common Cause: Rain, Snails, and the Rainbow

A typical example used in *Impossible Probability* to illustrate a **positive correlation without direct causality** involves the variables **rain**, **snails**, and the **rainbow**.

Empirically, it can be observed that **when it rains**, the **probability of seeing snails outdoors increases**—in other words, the **empirical probability** of snails appearing in open fields rises during rainy days. At the same time, the **probability of a rainbow appearing** also increases on rainy days, provided that sunlight breaks through afterward.

Hence, we observe a **positive correlation** between two phenomena—the presence of snails and the appearance of a rainbow—**even though no causal relationship exists between them**. Their correlation arises from a **common probable cause**, namely **rain**.

This is a classical example of **correlation by shared condition**: two independent phenomena exhibit **co-variation** because they are both influenced by the same **external factor**. In probabilistic terms, the two events share **conditional dependency** through the mediator variable "rain", the shared causal condition.

122.24. Medical Example: Independent Effects with Common Origin

A similar type of probabilistic correlation can appear in **medical research**. Suppose a clinical study is testing a **new pharmaceutical treatment** on a group of patients. During administration, researchers observe **two distinct effects** that occur more frequently within the treated group—effects that are **completely independent** of one another from a physiological standpoint.

This situation is analogous to the previous "snails and rainbow" example: the **same probable common cause** (the administered drug) may alter the **behavioral pattern of multiple independent variables**, thereby producing a **positive correlation** between them.

Even though one effect does not cause the other, their **joint frequency** increases due to their **common source of influence**. Consequently, their correlation can be studied statistically, without implying direct causation. This example demonstrates how **complex causal networks** may generate **apparent correlations** that stem from **shared probabilistic origins** rather than from direct interactions between variables.

122.25. Reciprocal Feedback Relationships Between Variables

Another important case is that of **mutual feedback relationships** (*retroalimentación mutua*) between variables. In such scenarios, it is **impossible to determine** which variable acts as the cause and which as the effect, since both **influence one another cyclically**.

Consider an educational setting: a teacher implements a **program to enhance mathematical intelligence** among students. Over time, the **language teacher** notices a concurrent **improvement in reading comprehension skills**.

Initially, the mathematics program was not designed to improve linguistic abilities. However, among its side effects might be the **enhancement of attention, symbolic comprehension, and abstract reasoning**—all of which can **indirectly benefit language processing** and thereby lead to **improved academic performance** in other subjects, such as reading and literature.

Conversely, if a school introduces a program to improve **reading comprehension**, the gains in linguistic precision and interpretive understanding may lead to **better problem-solving in mathematics**, especially in the comprehension of **verbal problem statements**.

Thus, **each domain reinforces the other**:

- Improvements in mathematical capacity enhance reading comprehension;
- Improvements in reading comprehension enhance mathematical reasoning.

This type of relationship exemplifies **bidirectional correlation through feedback**, where both variables evolve together in a **mutually reinforcing loop**.

122.26. The Probabilistic Interpretation of Feedback Systems

In *Impossible Probability*, feedback systems are modeled as **closed probabilistic structures** in which each variable simultaneously functions as both **independent and dependent**.

Rather than representing a linear chain of cause and effect, such systems operate as **recursive models**:

$$V_1 \rightarrow V_2 \rightarrow V_1$$

where changes in one variable generate proportional changes in the other, which in turn influence the first.

From a probabilistic standpoint, these feedback relationships are **dynamic equilibria**, in which the **empirical probabilities** of each variable's state evolve in continuous interdependence. This creates **self-stabilizing systems**, capable of generating **emergent order**—a direct application of the fundamental law of *Impossible Probability*: that ***stochastic interrelation is the mechanism by which rational order manifests within complexity***.

In this sense, *Impossible Probability* transcends both classical determinism and indeterminism, proposing a new synthesis where **causal symmetry and probabilistic recursion** become the true logical form of reality.

122.27. Mutual Feedback in Biological Ecosystems

In a biological ecosystem where equilibrium depends upon **collaborative interspecies relationships**, the adequate development of one species contributes directly to the adequate development of others.

For example, in a meadow where **floral diversity** depends on **bee pollination**, the **presence of a healthy bee population** becomes an indispensable condition for the **maintenance of the flower population**. Conversely, the **availability of flowers** is equally indispensable for the **survival and continuity of the bee population**.

In this type of system, it would be incorrect to describe one variable as the **cause** and the other as the **effect**. Rather, both variables **mutually sustain and reinforce** one another through a **reciprocal feedback mechanism**. ***The bees enable the reproductive success of flowers, while the flowers provide the sustenance necessary for the bees' survival.***

From a probabilistic standpoint, the empirical probability of either population's success is **directly dependent on the empirical probability of the other**. This interdependence exemplifies what *Impossible Probability* defines as a **bidirectional stochastic correlation**, where the state of one factor is probabilistically inseparable from the state of its counterpart.

Thus, ecosystems represent **natural feedback systems**, structured through **reciprocal dependencies** that maintain a dynamic but self-regulating equilibrium — a manifestation of **order emerging from probabilistic reciprocity**.

122.28. Dialectical Interconnection and Global Systemic Complexity

Within a **dialectical conception** of reality — one that recognizes the continuous transformation and interrelation of all things — every system is seen as a **totality of interconnected variables**. In such a framework, any modification in one variable can produce **system-wide changes** across multiple levels.

This global interconnectivity gives rise to a **complex stochastic network** of **multiple correlations**, where every element influences and is influenced by the others to varying degrees of intensity and directionality. The system thus becomes a **multilayered field of interdependent feedback loops**, each contributing to the **formation, transformation, and emergence of new phenomena**.

From the standpoint of *Impossible Probability*, this complexity is not merely descriptive but **structural**:

- Each variable participates simultaneously in multiple levels of correlation.
- The contribution of each factor is measurable in **probabilistic terms**.
- The emergence of a phenomenon represents the **empirical synthesis** of countless stochastic interactions.

Hence, the dialectical interpretation of reality aligns with the **probabilistic interpretation**: both recognize that the universe is not a static entity but a **dynamic process of interrelation and transformation**, governed by principles of **causal reciprocity** and **statistical emergence**.

This probabilistic dialectic constitutes a key philosophical foundation of *Impossible Probability*, establishing that **complex order arises from the dynamic equilibrium of interdependent variables** operating under the laws of chance and proportion.

122.29. The Philosophical Meaning of Variables: Constancy and Change

The concept of the **variable** occupies a **transcendental position** in scientific thought because its very definition encapsulates a profound **philosophical implication**.

To define reality as a **set of factors** — some constant, others variable — is to acknowledge that **reality itself is not immutable**. This recognition introduces a **dialectical structure** into scientific understanding: we distinguish between **that which changes (the variable)** and **that which remains (the constant)**.

In this dialectical relation, constancy provides **structural stability**, while variability introduces **dynamic evolution**. The interplay between the two defines the **motion of reality** and the **conditions of knowledge**.

Science, in this view, is not merely the observation of what exists, but the **systematic study of what changes** — of the variations, transformations, and probabilities that characterize phenomena. The essence of scientific inquiry, therefore, lies in the

quantification of change, in understanding how and why variables alter their empirical probabilities under different conditions.

In *Impossible Probability*, this principle is elevated to a central epistemological postulate:

The object of science is not permanence, but transformation — the probabilistic movement of variables within the field of reality.

This conception unites **dialectical philosophy** and **statistical reasoning** into a coherent framework, wherein **change is the manifestation of probability**, and **probability is the mathematical *language* of change**.

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Rubén García Pedraza
imposiblenever@gmail.com

123.Maximum Possible Theoretical Standard Score

123.1. The Concept of the Typical Score in the First and Second Methods

In traditional statistics—what *Impossible Probability* defines as the First Method—the *typical score* (or standardized score, commonly known as the *z-score*) is calculated as the differential score divided by the standard deviation. It expresses the number of standard deviations a particular measurement lies above or below the mean.

However, due to the conceptual redefinitions introduced in the Second Method of *Impossible Probability*, the formula for the typical score undergoes a fundamental transformation. In this framework, the *typical score* is defined as the Level of Bias (Nivel de Sesgo) divided by the Mean Deviation or Standard Deviation. This redefinition aligns the concept of standardization with the broader logic of *Impossible Probability*, where dispersion and deviation are understood in rational-proportional rather than purely empirical terms.

Formally:

$$\text{Typical Score (Second Method)} = \frac{\text{Level of Bias}}{\text{DMoS}}$$

where DMoS represents either Mean Deviation (*Desviación Media*, MD, in Spanish) or Standard Deviation (*Desviación Típica*, S, in Spanish), depending on the analytical context.

123.2. Preference for Mean Deviation in *Impossible Probability*

In *Impossible Probability*, the researcher is given the option to use Mean Deviation or Standard Deviation whenever a measure of sample dispersion is required. Nonetheless, the Mean Deviation is generally preferred.

The reasoning is both conceptual and mathematical:

- The Mean Deviation preserves the original differences between individual data points and the mean.
- The Standard Deviation, on the other hand, alters the sum of the total bias, since it squares each deviation, sums the squared values, and then takes the square root of the result.

While this quadratic operation enhances numerical stability in traditional statistics, it also distorts the proportionality of deviations. The Mean Deviation, by maintaining a linear relationship between bias values, offers a more faithful representation of empirical divergence.

Thus, the Mean Deviation better reflects the *qualitative sense of difference*—a principle central to the rational critique of reality in *Impossible Probability*.

123.3. The Maximum Theoretical Typical Score

When the typical score in the Second Method is conceptualized as the Level of Bias divided by the Mean or Standard Deviation, it becomes possible to define a Maximum Theoretical Typical Score.

This maximum corresponds to the highest possible theoretical probability, $p(x_i) = 1$, known as *Probability One*. It represents a state of complete certainty, the extreme limit of empirical probability. The formula for this condition is as follows:

$$\text{Maximum Theoretical Typical Score} = \frac{(1 - \frac{1}{N})}{\text{DMoS}}$$

where N represents the total number of subjects or options in the sample.

This formulation situates the typical score within a broader rational structure: it no longer expresses deviation from the mean merely in relative distance, but rather as a proportion of empirical bias over theoretical dispersion—an expression of how far a given observation deviates from theoretical equilibrium within the total system.

123.4. The Gaussian Curve and the First Method

The concept of the *typical score* originates in traditional statistics (the First Method), which interprets it as a positional indicator within the Gaussian bell curve (the *normal distribution*). In this classical model, the typical score identifies how far a data point lies from the mean, allowing researchers to determine the proportion of the area under the curve that corresponds to that position.

The Gaussian model assumes that most phenomena cluster around the mean, with fewer occurrences toward the extremes—hence, the term *normal distribution*. A distribution is said to be *normal* when most typical scores concentrate within one standard deviation above or below the mean.

While *Impossible Probability* acknowledges the descriptive usefulness of this model, it expands its interpretation: instead of being a fixed law of nature, the Gaussian curve becomes a representation of equilibrium tendencies within probabilistic systems. Thus, the “normal” is not a property of nature but a statistical approximation of stability.

123.5. The Mean of Empirical Probabilities and the Role of Bias

In the Second Method of Impossible Probability, the arithmetic mean of empirical probabilities corresponds to the theoretical probability, which is the inversion of N ($1/N$). This principle forms one of the core operational rules of the theory.

Consequently, the Level of Bias is defined as the difference between the empirical probability and the theoretical probability:

$$\text{Level of Bias} = p_e - \frac{1}{N}$$

The Maximum Theoretical Bias—that is, the greatest possible deviation between empirical and theoretical probabilities—is therefore expressed as:

$$\text{Maximum Theoretical Bias} = 1 - \frac{1}{N}$$

This condition is achieved only under circumstances of maximum dispersion, when within the entire sample N, only one subject or option possesses a nonzero empirical probability, while all others ($N - 1$) have empirical probability zero.

Under such extreme conditions, we also obtain the Maximum Theoretical Mean Deviation, the Maximum Theoretical Variance, and the Maximum Theoretical Standard Deviation.

123.6. Deriving the Maximum Theoretical Mean Deviation

Under conditions of maximum dispersion, the Maximum Theoretical Mean Deviation is derived as the mean (or product by $1/N$) of the Total Bias under such extreme conditions.

Formally, this can be expressed as the mean of the sum of the Maximum Theoretical Bias plus the product of the inversion of N by (N – 1):

$$\text{Maximum Theoretical Mean Deviation} = \frac{[(1 - \frac{1}{N}) + (\frac{1}{N} \cdot (N - 1))]}{N}$$

This formula can also be represented equivalently as:

$$\text{Maximum Theoretical Mean Deviation} = \frac{2(1 - \frac{1}{N})}{N}$$

In *Impossible Probability*, this simplified version is the one most frequently used, representing the average of the double of the Maximum Theoretical Bias divided by the total number of elements N.

Thus:

$$\text{Maximum Theoretical Mean Deviation} = \frac{[(1 - 1/N) \cdot 2]}{N}$$

123.7. The Maximum Theoretical Variance and Standard Deviation

The Maximum Theoretical Variance is obtained by calculating the mean (or multiplying by $1/N$) of the sum of the squared Maximum Theoretical Bias plus the product of the squared inversion of N by (N – 1):

$$\text{Maximum Theoretical Variance} = \frac{[(1 - \frac{1}{N})^2 + ((\frac{1}{N})^2 \cdot (N - 1))]}{N}$$

From this, the Maximum Theoretical Standard Deviation is derived as the square root of the above expression:

$$\text{Maximum Theoretical Standard Deviation} = \sqrt{\frac{[(1-\frac{1}{N})^2 + ((\frac{1}{N})^2 \cdot (N-1))]}{N}}$$

These formulas define the upper boundary of dispersion theoretically attainable within a probabilistic system governed by finite N.

123.8. The Preference for Mean Deviation in Hypothesis Testing

Once the Maximum Theoretical Probability, Bias, and measures of dispersion (Mean Deviation, Variance, and Standard Deviation) are known, *Impossible Probability* enables the computation of Maximum Theoretical Typical Scores under both metrics.

When calculated using Mean Deviation, the formula becomes:

$$\text{Maximum Theoretical Typical Score (Mean Deviation)} = \frac{(1-\frac{1}{N})}{[(1-\frac{1}{N}) \cdot 2]/N}$$

When calculated using Standard Deviation, it is expressed as:

$$\text{Maximum Theoretical Typical Score (Standard Deviation)} = \frac{(1-\frac{1}{N})}{\sqrt{[(1-\frac{1}{N})^2 + ((1/N)^2 \cdot (N-1))]/N}}$$

Both expressions are valid, but as previously explained, the Mean Deviation is preferred whenever feasible, since it maintains the linearity of differences and avoids the artificial expansion of variance inherent in quadratic transformations.

123.9. Reformulating Hypothesis Testing in the Second Method

Knowing the Maximum Theoretical Typical Score allows the reformulation of hypothesis testing models within *Impossible Probability*.

Unlike the First Method, where hypothesis testing depends on the cumulative area under the Gaussian curve, the Second Method enables direct comparison between the typical score of any subject or option and the Maximum Theoretical Typical Score, both computed with respect to the same measure of dispersion (Mean or Standard Deviation).

This transformation eliminates the need to rely on tabulated areas of the normal distribution. Instead, hypothesis contrasts become rational-proportional comparisons, establishing direct quantitative relationships between observed deviations and their theoretical maxima.

Such comparisons—whether differential or quotient-based—constitute a more general and abstract approach to statistical reasoning, enabling the critique of empirical reality through rational measurement of bias and dispersion, as fully developed in Section 15 of *Introduction to Impossible Probability: Statistics of Probability or Probabilistic Statistics*.

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Rubén García Pedraza
imposiblenever@gmail.com

124. Sample of two options

124.1. Definition of a Two-Option Sample

A **two-option sample** is one in which the total number of possible subjects or options (N) is limited to only **two alternatives**. This applies to both natural and social sciences.

For instance, when we **toss a coin**, the possible outcomes are **heads or tails**. In **human biology**, an individual may be classified as **male or female**. In **quantum physics**, a photon may be studied as behaving either as a **wave or a particle**, and in **electrical physics**, the charge of a particle is either **positive or negative**.

However, even such apparently binary systems admit exceptions. A coin may, in rare circumstances, **land balanced on its edge**, thus being neither heads nor tails. A human being may be **intersex** rather than strictly male or female. A photon may **exhibit dual behavior**, simultaneously as a wave and a particle, and in addition to positive and negative charges, **neutrons** exist as electrically neutral particles.

Thus, even though reality is not reducible to purely binary dimensions, under certain experimental or observational conditions, **samples of only two possible outcomes** are useful or necessary. These constitute the **paradigm of the limited universe**, a universe restricted to only two possible options.

124.2. The Concept of a Limited Universe of Options

A **limited universe of options** is one in which the object of measurement is the **count of occurrences** corresponding to each possible option. The **total number of occurrences** across all options constitutes the **overall frequency**, and by definition, such a universe **does not tend toward infinity**.

The number of available options in such a system is equal to the sample size, **N**, and the **empirical probability** of each option is defined as the **frequency of that option divided by the total frequency**.

It is within these limited universes that the empirical probability defined by the **Second Method of Impossible Probability** most closely resembles the **classical notion of relative frequency** from traditional statistics (the First Method).

However, even in this superficial resemblance, there is **no conceptual equivalence**. In *Impossible Probability*, **empirical probability** is calculated not simply as the ratio of occurrences but as the **ratio of direct scores or frequencies** of each subject or option relative to the **sum of all direct scores or frequencies**.

Whereas traditional frequency counts only discrete occurrences, the **direct score** in the Second Method represents the **magnitude or intensity of a measured quality** within each subject or option. This difference makes the Second Method a far more general and flexible framework for representing real phenomena.

124.3. Empirical Probability and the Equivalence of Subjects and Options

One of the major conceptual advances in *Impossible Probability* is that the **empirical probability** treats the notions of **subject** and **option** as **formally equivalent**.

In this way, **all types of data**—whether derived from direct measurement or frequency counts—are processed using a **single rational formula**:

$$p_e(x_i) = \frac{x_i}{\Sigma x_i}$$

where $x_i$represents the direct score or frequency of a subject or option.

This equation unifies all empirical measures under the same mathematical structure, enabling the extension of probability beyond discrete events to **continuous magnitudes** and **qualitative intensities**, a central innovation of the Second Method.

Thus, empirical probability becomes the **fundamental descriptor of reality**, applicable across domains from the physical sciences to social behavior.

124.4. Universes of Options and Universes of Subjects

Once the distinction between **relative frequency** (First Method) and **empirical probability** (Second Method) is established, *Impossible Probability* identifies two types of universes:

1. **Universes of Options**, which are inherently **limited**, with a finite number of discrete choices.
2. **Universes of Subjects Treated as Options**, which may be **potentially infinite**, particularly in population or temporal studies.

In universes of options, N defines **the absolute limits** of the system. In universes of subjects, N can, in principle, increase indefinitely—reflecting the **open, evolving nature of empirical reality**.

Even when a study is temporally or spatially limited, the potential number of measurements within that range can approach infinity, which necessitates the introduction of **sample representativity and error probability**, quantified as $1/N$.

124.5. Discrete Universes and Categorical Studies

Within the domain of **limited universes**, the number of possible options defines the **boundaries of that universe**. This includes universes formed from natural categories (such as biological sex or particle charge) and **social categories** (such as civil status or political affiliation).

In statistical research, such universes often take the form of **discrete categorical systems**, where a scale of magnitude is divided into defined **intervals** according to upper and lower bounds.

Each category contains the number of events or subjects whose measurement falls within its interval, and the **sum of all category frequencies** equals the total sample frequency.

These discrete universes are a cornerstone of empirical classification in *Impossible Probability*, as discussed in **Section 10 of Introduction to Impossible Probability**, where they are described as **bounded universes of limited options**.

124.6. Examples of Limited Universes

A few practical examples clarify the concept:

- A **six-sided dice** constitutes a **universe of six options**.
- In **social science**, a person's **marital status** (single, married, separated, divorced, widowed) represents a **five-option universe**.

Although the number of options may vary, the universe remains **finite**. The smallest possible universe has **two options**—the minimal N required for stochastic study.

If fewer than two options exist, no probabilistic comparison can occur, and therefore, **no stochastic model** is possible. Hence, **N = 2** represents the **minimum condition for statistical existence**.

124.7. Properties of the Two-Option Universe

The two-option universe, as the **minimum empirical structure** capable of sustaining stochastic analysis, possesses unique properties.

For any two-option sample, the **arithmetic mean** of the probabilities is always **0.5**. Unless both options share equal empirical and theoretical probabilities, **any minimal bias** will result in each option displaying a **Maximum Possible Empirical Bias** equal to **Total Bias divided by N**, which in this case equals **Bias/2**.

Under conditions of **maximum dispersion**—when one option has a probability of **1** and the other **0**—the **Mean Deviation** is also **0.5**.

Thus, in universes of two options, the **inversion of N (1/N)**, representing theoretical probability, coincides not only with the **arithmetic mean** but also with the **Maximum Theoretical Mean Deviation** and the **Maximum Theoretical Standard Deviation**.

This convergence demonstrates that in a two-option universe, **the mean and the maximum theoretical dispersion** share the same magnitude.

124.8. The Logic of Tendency and the Concept of N

Throughout *Introduction to Impossible Probability*, the analytical framework employed in developing the theory is referred to as the **syllogism of tendency**—the application of logic to the study of how systems approach their limits.

When applying this reasoning to the variable N (the total number of subjects or options), the logical conclusion is immediate: **N is a variable bounded between two and infinity**.

- **Two** represents the minimum necessary for any stochastic relationship.
- **Infinity** represents the theoretical limit of open universes.

In practice, research in universes of subjects always operates with a finite **sample (N)** that approximates the behavior of larger or infinite systems. Such samples must be **large enough** to be both **representative** and **mathematically operational**.

124.9. The Inoperability of Infinite Samples

Mathematically, an **infinite sample** is **inoperative**.

If N tends to infinity, its inversion (1/N)—which defines theoretical probability—tends toward **zero**. Consequently:

- The **empirical probability** also tends toward zero.
- Both the **empirical and theoretical probabilities** become zero, making any calculation of tendency impossible.

This produces a logical contradiction: the mathematical model implies an absence of variability, whereas the **real universe is not devoid of fluctuation or difference**.

Furthermore, when N → ∞, both the **Maximum Theoretical Mean Deviation** and the **Maximum Theoretical Standard Deviation** also tend toward **zero**, implying a paradoxical collapse of dispersion in systems that, in reality, remain highly dynamic.

124.10. Limits of Dispersion: From N = 2 to N → ∞

When N = 2, the **Maximum Theoretical Mean Deviation** and the **Maximum Theoretical Standard Deviation** both equal **0.5**, the greatest possible value of dispersion.

As N increases, these values **decrease monotonically**, tending asymptotically toward **zero** as N approaches infinity. Thus, these measures are **functions of N**, with their highest possible value occurring at the minimum N = 2.

Similarly, theoretical probability $1/N$ behaves as a **dependent variable** of N: its maximum value is **0.5** (when N = 2), and it decreases toward zero as N → ∞.

Therefore, both theoretical probability and the two maximum theoretical dispersion statistics are **dependent on N** and share the same upper boundary of **0.5**.

124.11. The Convergence of Probability and Dispersion in Their Extremes

Only at their **extreme limits** do the theoretical probability (1/N) and the two maximum theoretical dispersion measures coincide in value:

- When **N = 2**, all three equal **0.5**.
- As **N → ∞**, all three tend toward **0**.

In the first case, this reflects **maximum contrast** between options (complete differentiation). In the second, it expresses **complete homogeneity** within infinite universes.

Thus, as N increases, *Impossible Probability* predicts a **convergent asymptotic reduction** of both probability and dispersion—mirroring the structure of universes where order emerges through the statistical diminution of difference.

124.12. Final Implication: The Rational Boundaries of N

Ultimately, N defines not only the **scope of possible options** but also the **rational limits of representation**.

The smaller the N, the higher the potential for **empirical contrast** and **maximum dispersion**. The larger the N, the stronger the **tendency toward theoretical equilibrium**.

This dialectic—between minimal duality (N = 2) and infinite continuity (N → ∞)—represents one of the central logical structures of *Impossible Probability*.

It demonstrates that both **probability** and **dispersion** are not fixed attributes of reality but **rationally dependent magnitudes**, whose variation reflects the **relational nature of existence** itself:

Intelligence = The capacity to relate.

In this way, *Impossible Probability* establishes a mathematical expression for the **universal law of relationality**, showing that every form of empirical knowledge arises from the **measurable interplay between finite contrast and infinite tendency**.

This augmented translation is based on the post
published in *https://probabilidadimposible.blogspot.com/*,
On 14 November 2015,
Rubén García Pedraza
imposiblenever@gmail.com

125. Independent variable

125.1. What a Variable Is: Measurability, Sampling, and Hypothesized Causality

A **variable** is a **measurable factor of study**—a property or quality that can be quantified. From this quality we may extract a **set of observations (a sample)** by measuring either (a) the **intensity** of the quality across multiple **subjects or options**, or (b) the **frequency** or **direct scores** obtained through **repeated measurements** on the same entity. A variable is defined, at least in theory, by the hypothesis that—**not being constant**—it may possess a **degree of causal contribution** to the occurrence or variation of other phenomena, traditionally termed **dependent variables**.

125.2. The Classical View: Independent vs. Dependent Variables

In **classical experimental statistics**, the **independent variable** is the factor **actively manipulated** by the researcher to observe its **effects** on **dependent variables**. Thus, the primary distinction is operational: the **independent** is **manipulated**; the **dependent** is **observed** as an outcome.

- **Medicine:** independent = treatment protocol; dependent = patient symptom trajectory.
- **Pedagogy:** independent = instructional method; dependent = academic achievement.
- **Astrophysics:** independent = experimental manipulation of particles; dependent = observed particle behavior.

In general, the independent variable is that upon which the **research team intervenes**, and the dependent variable is that in which the **consequences of intervention** are measured.

125.3. Beyond the Classical Frame: New Epistemologies and Methods

The classical definition retains validity **where the traditional experimental method is feasible**. Yet twentieth-century advances in **epistemology** and **methodology** led to new distinctions, most notably the emergence of the **quasi-experimental method** in the social sciences and the reformulation of foundational concepts under the influence of **uncertainty, relativity, chaos, and complexity**. These developments motivate **revised definitions** of independent/dependent variables that are sensitive to **contextual constraints**, **limited manipulability**, and **nonlinear dynamics**.

125.4. Variables in Probabilistic Statistics: From Determinism to Stochasticity

When probability statistics operates within **stochastic sciences**, the classical presumption that every effect has a single, clearly tractable cause is **dissolved** into **multicausal complexity**. The apparent linearity of cause–effect chains gives way to **networks of interacting factors**. In such contexts, it is often more accurate to investigate **probable causes** rather than to assert **strict determinism**.

[Beside this, it is necessary to highlight the complexity of reality itself, especially under quasi experimentation conditions, where more than independent variables we manipulate interdependent variables in complex contexts.]

125.5. From Laplacian Determinism to Indeterministic Models

Against **deterministic probability models**—whose emblem is **Laplace**—the twentieth century elaborated **indeterministic models** in statistics and probability. These frameworks acknowledge that **randomness**, **nonlinearity**, and **sensitive dependence on initial conditions** can **alter or overwhelm** simple cause–effect sequences [butterfly

effect, what in London could be named snowball effect]. The distribution of phenomena may be **chaotic**, and causal attribution becomes a matter of **probabilistic weight** rather than necessity.

125.6. Section 13's Cosmological Thesis: Order From Random Accidents

Section 13 of *Introduction to Impossible Probability* develops a **cosmological conception**: from **random accidents** arise **contingencies** that **stabilize** into **regular patterns**. Collisions of cosmic dust and matter generate **celestial bodies, galaxies, and planets**; within planets, **geological and atmospheric dynamics** emerge; on Earth, **life** appears and evolves through **random biological combinations** interacting with **geological and climatic accidents** (including **mass extinctions** and **meteor impacts**). In time, these processes create conditions for **human life** and, through further contingencies, for **complex societies**.
Social history mirrors natural history: a succession of accidents gives rise to **stable regularities**, until new accidents create **new conditions**, **new contingencies**, and **new patterns of orderly movement** of matter and energy in space-time. This, in brief, is **history** viewed probabilistically: **order as an emergent property of stochastic processes**.

125.7. Methodological Consequences: Causality as Probabilistic Attribution

In such a world, the independent/dependent distinction becomes **context-relative**. When **direct manipulation** is possible (laboratory experimentation), the classical definition holds. When manipulation is **limited or impossible** (field research, social systems, astrophysical events), we rely on **quasi-experimental** or **observational** designs. Causality is then **attributed probabilistically** through **empirical probabilities**, **theoretical benchmarks**, and **bias measures**, rather than asserted as a strict chain.

125.8. Operationalization in *Impossible Probability*: Empirical vs. Theoretical

Within the **Second Method** of *Impossible Probability*:

- Each observation becomes an **empirical probability** $p(x_i) = x_i/\sum x_i$, derived from **direct scores or frequencies**.
- The **theoretical probability** is $1/N$, the **inversion of N**, serving as a **rational baseline**.
- **Level of Bias** = $p(x_i) - 1/N$; quantifies **departure from theoretical equilibrium**.

This scheme makes **variation** (not merely raw frequency) the **object of analysis**, aligning causal inference with **rational proportions** rather than with presumed linear mechanisms.

125.9. Designing Research Under Stochastic Conditions

Under stochasticity, robust design emphasizes:

1. **Explicit limits on manipulability** (experimental vs. quasi-experimental conditions).
2. **Multicausal modeling** (allowing multiple, possibly interacting contributors).
3. **Bias-based metrics** (contrasting empirical with theoretical probabilities).
4. **Error structures** (recognizing residual variance and measurement limits).
5. **Replicability as probabilistic** (stability across contexts is **evidential**, not absolute).

125.10. Science as the Study of Transformations

In sum, a variable is not merely a **measurable attribute**; it is a **candidate contributor** to patterns that **emerge** from randomness and **stabilize** into order. The classical pair—independent and dependent—remains **methodologically useful** where manipulation is feasible, but contemporary science—especially as articulated in *Impossible Probability*—understands variables within **stochastic, multicausal, and *often* nonlinear systems**.
Science thus becomes the **rational study of transformation**: measuring how variables **deviate** from theoretical equilibrium, how **bias accumulates or cancels**, and how **order emerges** from the **probabilistic interplay** of countless contingent events.

125.11. The Problem of Absolute Causality in Indeterministic Models

Within an **indeterministic model** such as *Impossible Probability*, any **absolute or apodictic attribution of causality** to an independent variable becomes **philosophically and empirically questionable**.

In a universe governed by **the laws of chance**, or what the theory calls the **law of probabilities**, the natural law, every assertion of universal causality is subject to a **margin of rational doubt**. The only truly universal law is, paradoxically, the **law of probability itself**—that all phenomena are subject to ***uncertainty and statistical fluctuation, the natural order***.

Hence, the only **logical relationship** that can consistently be established between one variable and another is a **probabilistic relationship**, not necessarily a **causal** one. In many cases, such relationships may instead be characterized by **simultaneity**, **mutual interaction**, or **feedback** rather than strict cause and effect.

125.12. Simultaneity, Coincidence, and the Limits of Causal Inference

The mere **temporal coincidence** of two variables—whether simultaneous or sequential—does not suffice to establish causation, even if the association is **repeatedly observed**.

For example, suppose in a medical study a particular treatment produces **two distinct observable effects**. Unless there is **compelling empirical evidence** demonstrating a causal link between these two effects, there is no sufficient rational justification for inferring such a relationship.

Furthermore, the relationship between the **treatment** and its **effects** must always be interpreted within a **margin of rational uncertainty**, proportional to the **accepted margins of error** that define the boundaries of scientific validity.

This distinction preserves the essential epistemological humility of *Impossible Probability*: causal interpretation is **conditional**, never absolute, and always **bounded by probability**.

[As Hume stated, causality is a belief produced by custom. This is why we need to maintain a margin of skepticism: causality is a psychological construct, not necessarily a reflection of reality. It is what our brain is programmed to believe after observing repetitive patterns—but this is merely a **physiological outcome of the brain**, not necessarily an objective truth. As Hume stated, the fact that the sun rises every morning does not mean we should deduce that it will always do so; it is merely a repetitive pattern transformed into a **psychological expectation** of the brain. That is all.]

125.13. Two Fundamental Types of Error in *Impossible Probability*

The theory distinguishes between two fundamentally different forms of error: the **factual error (error de hecho)** and the **rational error (error racional)**.

125.13.1. Factual Error: The Error of Representation

In *Introduction to Impossible Probability: Statistics of Probability or Probabilistic Statistics*, the **factual error** is defined as the **error we implicitly accept the moment we accept any empirical sample as representative of reality**.

To accept reality as such is already to **accept an error**, because every empirical observation is a **partial representation** of the totality.

The **error of sample representativity** is mathematically defined as the **inversion of the sample size**.

- In **universes of infinite subjects or options**, the **probability of representational error** is simply $1/N$.
- In **limited universes of options**, the **probability of representational error** equals the **inversion of the sum of all direct scores or frequencies**, expressed as $1/\sum x_i$.

This formulation shows that **sampling error** is an unavoidable epistemic condition of measurement—*to know empirically is always to know within error.*

125.13.2. Rational Error: The Error of Acceptance

The **rational error** is the **margin of uncertainty that reason itself accepts** when it approves a hypothesis as provisionally valid within a probabilistic framework.

In statistical inference, this corresponds to the **critical probability**—the threshold used in hypothesis testing.

Whether one operates within a **margin of confidence (reliability)** or a **margin of error**, the rational act of acceptance implies a recognition that the hypothesis is true **only within the limits** defined by that margin.

Mathematically, this can be expressed as:

- **Margin of error** = X% of possible error out of 100.
- **Margin of confidence** = 100% – X% of error= reliability .

Thus, rational error represents the **intellectual tolerance of uncertainty**, a philosophical as well as mathematical acknowledgment that all empirical truth is **probabilistic truth**.

125.14. The Probabilistic Nature of Causal Relationships

Under this epistemological framework, the relationship between a **treatment** (independent variable) and its **effects** (dependent variables) must always be expressed as a **probable causal relation**—a relation subject to an **uncertainty proportional to the margin of error and the sample error**.

There is always sufficient space for doubt, meaning that **universal acceptance** of an independent variable as a general causal law must be **qualified by rational limits**. In practice, this means that the independent variable may fail to produce the expected effect in certain cases, owing to **individual, environmental, or systemic contingencies**.

[It is here, within the boundaries of the margin of error or the sampling error, that we control—within rational limits—our **skepticism** (Hume), our **doubt** (Descartes), and our **uncertainty** (Heisenberg). In essence, skepticism, doubt, and uncertainty are different ways of confronting reality: different methods of managing our **ignorance about what is truly happening**. In the same way, we can say that it is **within the rational limits of the margin of error** where any truth becomes relative—since it is already, in part, false within the very margin of error that we have already accepted.]

125.15. Conditional Universality and the Limits of Rational Acceptance

Suppose a medical study on N subjects excludes patients with specific **genetic profiles**, **pre-existing conditions**, or **drug intolerances**. Once the treatment is administered to individuals with such profiles, the **error rate** of the treatment increases substantially.

Consequently, the treatment cannot be considered **universally effective**, and its rational universality becomes **relative to the probability of both factual and rational error**.

This is a key insight of *Impossible Probability*: **universality is a probabilistic construct**, never absolute. Every law, every relationship, every conclusion exists **within its own rational margin of error**.

[In this scenario, we can say that the **universal validation of a treatment** applies only to the **universe of subjects** who meet the criteria of the sample in which the treatment was tested; **beyond this universe**, the treatment becomes **invalid**.]

125.16. The Fallacy of Spurious Correlation

Another critical implication is that any **causal attribution** between **simultaneous or sequential phenomena**, when not supported by sufficient rational evidence of a **probable causal relationship**, is **unfounded**.

This type of misattribution—known as **spurious correlation**—is a recurring error in scientific reasoning. It occurs when two phenomena appear related purely due to **coincidence** or **hidden variables**, even though **no formal or necessary relation** actually exists between them.

Impossible Probability treats such cases as examples of **false causation by simultaneity**, where human perception of pattern substitutes for actual probabilistic structure.

125.17. Causality as a Function of Probability

Impossible Probability replaces the metaphysical notion of **causal necessity** with the epistemological principle of **probabilistic causality**.

Every apparent cause-and-effect relation is, at its core, a **statistical tendency**, a **pattern of conditional probability** that reflects—but does not determine—the organization of reality.

Thus, the **law of probability** becomes the **law of laws**, the universal condition under which all other regularities are observed.

Absolute causality dissolves into **relational probability**, and certainty transforms into a **rational measure of doubt**—the essential foundation of scientific realism in an indeterministic universe.

125.18. Feedback Relationships and the Limits of Classical Causality

Another type of relationship that cannot be accommodated within the **classical concept of an independent variable** is the **feedback relationship**.

When two variables **mutually influence** one another, or when **negative entropy dynamics** operate within the system, any attribution of cause and effect in the traditional linear sense becomes **conceptually meaningless**.

125.19. Reciprocal Relationships in Educational Research

Numerous educational studies have demonstrated that the improvement of **mathematical abilities** enhances the **symbolic comprehension capacity** of students, which can, in turn, improve their **reading comprehension**.

Conversely, the improvement of **reading skills** can positively influence **mathematics performance**, since students better understand the **verbal formulations** and **symbolic language** used in mathematical problems.

In synthesis, **mathematical and linguistic competences are interconnected**, forming a **system of reciprocal reinforcement**. Such systems exemplify **feedback relations**, where each variable enhances the development of the other rather than existing in a one-way cause–effect hierarchy.

This perspective moves beyond the rigid determinism of early experimental statistics and aligns with the **systemic logic** of *Impossible Probability*, where **variables co-evolve** through **interactional feedback** and **mutual adjustment** rather than through isolated manipulation.

125.20. Expanding the Modern Meaning of the Independent Variable

Although statistical textbooks still define the **independent variable** in its **classical experimental sense**—as "the variable that is manipulated in order to observe its effects on the dependent variable"—the concept today must be understood in a **broader and more inclusive framework**.

In contemporary research, the term **independent variable** extends far beyond the scope of **experimental manipulation**. It now designates **any factor** whose **effects upon other variables** are to be examined, regardless of whether direct control or manipulation is possible.

[And, more importantly, in contemporary science we understand that a first non manipulable variable may be **independent** in relation to a second variable, yet the same first variable can be **dependent** on a third variable. This occurs within an **ecosystem of complex interdependent variables**, where every variable interacts with others, forming intricate **networks of dependency**.]

This conceptual shift is essential for modern fields such as **astrophysics**, **ecology**, **sociology**, and **environmental sciences**, where **controlled experimentation** is often **impossible** or **ethically restricted**, but **probabilistic inference** remains feasible.

125.21. The Case of Non-Manipulable Independent Variables

To illustrate this shift, consider the following examples:

- In a study examining how **solar storms** affect **atmospheric and climatic phenomena** on Earth, the **independent variable** would be **solar storms**, while the **dependent variables** would be the observed **terrestrial effects**. Yet, in this context, it is **impossible to manipulate** the independent variable; solar activity cannot be experimentally induced or controlled [**solar activity** itself is a **dependent variable**, influenced by other internal variables within the Sun—such as magnetic field dynamics, plasma flow patterns, and nuclear fusion cycles.].
- In another study investigating the **impact of bee populations** on **forest biodiversity**, one may establish correlations between **bee population density**, **plant diversity**, and **faunal diversity**. Here, the **base variable**—bee population—functions as the independent variable, even though it is not an object of experimental manipulation unless zoologists **artificially increase bee populations** through apicultural interventions or controlled relocation.

Thus, the **independent variable** in such cases is not defined by **experimental control**, but by its **theoretical role in the causal structure** of the phenomenon.

125.22. The Independent Variable as a Probable Cause Within Multicausal Systems

In modern scientific epistemology, the independent variable should therefore not be understood **solely** as the **manipulated variable** but as **the variable whose effects on other variables are studied**, regardless of experimental design.

Moreover, the independent variable is rarely the **exclusive cause** of any phenomenon. It is, rather, one of several **probable causes**—a **covariable** operating within a **multifactorial system** of interaction.

Hence, the notion of **independent variable** is redefined as a **covariable of effect**, especially in **multicausal** or **multifactorial models** where several variables jointly influence an outcome.

Each covariable contributes a **quantifiable percentage of causal probability**, representing its **relative weight** in the emergence of the observed phenomenon.

125.23. The Empirical Probability of Combined Factors

In nature, countless phenomena result from the **combination of multiple interacting factors**, and the **empirical probability** of a phenomenon is, in fact, the **probability of that combination occurring**.

For example, when studying the probability of a **rainbow** forming during rainfall, what is being measured is the **probability that the necessary combination of rain and sunlight** co-occurs at the right angles to produce the optical effect.

Similarly, in social sciences, when evaluating complex conditions such as **social well-being**, **employment rates**, **per-capita income**, and **educational levels**, each factor can be assigned a **percentage of contribution** to the overall state of well-being.

The phenomenon's empirical probability thus corresponds to the **probability of coexistence** or **joint occurrence** of these contributing factors within a defined temporal and spatial domain.

125.24. Quantitative Modeling of Multicausal Systems

When multiple variables interact to produce a single outcome, the **probability of the phenomenon** is the **probability of the joint combination** of the factors that make it possible.

This can be modeled quantitatively through **weighted factors**, where each variable contributes a measurable **percentage of causal influence**.

Such models are particularly applicable in **quasi-experimental designs**, where direct manipulation is absent but **comparative analysis** allows for the estimation of **relative contributions**.

For example, in a quasi-experimental study of **social well-being across nations**, one would:

1. Identify the contributing factors (employment, education, income, etc.),
2. Measure their respective empirical probabilities, and
3. Compare the resulting combinations across units of analysis (countries).

In this framework, each **independent variable** functions as a **covariable** whose influence is assessed **probabilistically**, forming part of an interdependent system where causality is **distributed**, not isolated.

125.25. Synthesis: From Deterministic Causation to Probabilistic Co-Variation

In conclusion, *Impossible Probability* redefines causality as **co-variation under uncertainty**.

Rather than assuming one-way determination, it conceives of phenomena as **emergent results of probabilistic combinations** of factors, each contributing with a **specific weight of empirical probability**.

The **independent variable**, therefore, is not a singular determinant but a **probabilistic participant** within a **system of dynamic interrelations**—a network of causes that are themselves effects, and of effects that act as new causes.

[Besides this, an **independent variable** can, at the same time, be a **dependent variable** of another, third variable—illustrating the **relational nature** of causality within complex systems.]

This transition from **deterministic causation** to **probabilistic interaction** marks a fundamental shift in scientific reasoning: it situates knowledge not in the discovery of

immutable laws but in the **quantification of relational probabilities** through which reality continuously reorganizes itself.

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Rubén García Pedraza
imposiblenever@gmail.com

126. Maximum Empirical Probability

126.1 Definition of the Maximum Empirical Probability

Once all empirical probabilities of every subject or option in the sample have been calculated, the **maximum empirical probability** is defined as the greatest of all these values.

In a sample *N* composed of subjects or options, after having determined *a priori* the empirical probability of each individual subject or option, the empirical probability that reaches the highest value in the entire sample will be called the **maximum empirical probability**, or simply **the maximum**.

In *Impossible Probability*, this statistical measure is represented by the symbol:

$$p(x_i^+) = \text{maximum possible empirical probability}$$

Hence, $p(x_i^+)$designates the **highest empirical probability observed** within a given sample *N*, and its meaning is purely empirical—it arises from observation and measurement rather than theoretical definition.

126.2 Distinction Between Maximum Empirical and Maximum Theoretical Probability

In *Introduction to Impossible Probability*, whenever the term **maximum empirical probability**, **maximum empirical**, or simply **the maximum** is used, it refers specifically to the highest empirical probability observed within the total sample of empirical probabilities.

This value must not be confused with the **Maximum Theoretical Probability Possible**, that is, probability equal to one (1). [Normally I called it Maximum Empirical Probability

Possible, as I said in the comments of another posts, in reality it is theoretical. It is difficult to explain why sometimes I called it empirical, most of the time, but exceptionally sometimes I called it theoretical.]

From a theoretical standpoint, probability is a dimension that oscillates between zero (0) and one (1). Therefore:

- Probability = 1 represents the **Maximum Theoretical Probability Possible**,
- Probability = 0 represents the **Minimum Theoretical Probability Possible**.

In studies of **positive bias**—those aimed at maximizing dispersion—the objective of research is for the ideal subject or option to achieve the maximum theoretical limit, $p = 1$, while all other options tend toward the minimum theoretical limit, $p = 0$.

Under these conditions of maximum dispersion:

- The **Mean Deviation** tends to its **Maximum Theoretical Mean Deviation**,
- The **Standard Deviation** tends to its **Maximum Theoretical Standard Deviation**.

126.3 Relationship Between Empirical and Theoretical Maxima

Except in the rare case where a subject or option exhibits a probability equal to one (that is, reaches the theoretical maximum), the values of empirical probabilities in most samples oscillate between zero and one.

Therefore, the maximum empirical probability $p(x_i^+)$, even though it represents the highest observed probability in the sample, does not necessarily equal one—it remains **below the Maximum Theoretical Probability Possible**.

However, even if $p(x_i^+)$is below one, it must always be **greater than the theoretical mean probability**, represented by the **reciprocal of N**, that is, $1/N$.

126.4 Range of Oscillation of the Maximum Empirical Probability

By definition, the **maximum empirical probability** is the probability that attains the greatest empirical value in the sample.

It differs from the **maximum theoretical probability (1)** because while the latter is an ideal theoretical limit, the empirical maximum reflects real, observable conditions.

Thus, the **range of oscillation** of the maximum empirical probability can be formally expressed as:

$$1/N < p(x_i^+) \leq 1$$

This means:

- The lower bound of $p(x_i^+)$is slightly above the mean theoretical probability $1/N$;
- The upper bound may approach (but not exceed) the theoretical limit of 1.

When all empirical probabilities in a sample are equal to $1/N$, **no empirical maximum** can be said to exist, since all values coincide with the theoretical mean. Consequently, both **Mean Deviation** and **Standard Deviation** would be the inversion of N, 1/N—an idealized model of perfect equality.

126.5 Existence of Maximum Empirical Probability in Biased Models

The concept of maximum empirical probability acquires practical relevance in **normal models of positive bias**.

In these cases, at least one subject or option exhibits a probability greater than the theoretical mean $1/N$. This higher value, $p(x_i^+)$, functions as the **empirical maximum**, indicating that there exists some empirical inequality or hierarchy of outcomes.

The **Normal Level of Positive Bias** of the maximum empirical probability is then:

$$p(x_i^+) - \frac{1}{N}$$

And as $p(x_i^+)$approaches 1, the **Level of Bias** approaches its upper theoretical limit:

$$\text{Maximum Theoretical Bias Possible} = 1 - \frac{1}{N}$$

Thus, when $p(x_i^+) = 1$, the bias reaches its theoretical maximum; when $p(x_i^+) = 1/N$, the bias equals zero, representing perfect equality.

126.6 Range of Oscillation of the Bias Level

In general, the **Normal Bias Level** of the maximum empirical probability is bounded by:

$$0 < (p(x_i^+) - 1/N) \leq (1 - 1/N)$$

That is:

- The minimum possible value (0) corresponds to perfect equality ($p(x_i^+) = 1/N$),
- The maximum possible value $(1 - 1/N)$corresponds to maximum inequality ($p(x_i^+) = 1$).

Therefore, the **Level of Positive Bias** is a variable dependent on *N* and the relative distance of the maximum empirical probability from the theoretical mean.

126.7 Dependence on the Magnitude of the Sample (N)

The magnitude of *N*—the total number of subjects or options—is crucial for understanding how the bias behaves.

Since *N* must always be greater than or equal to 2 for stochastic analysis, the **lower bound** of *N* is 2 (a universe with two possible options), and the **upper bound** tends toward infinity (a universe of infinite subjects or options).

Depending on whether the universe is **finite** (limited options) or **infinite**, the value of $1/N$ and consequently the range of the bias change considerably.

In finite universes:

- The theoretical mean $1/N$ has a defined positive value,
- The maximum theoretical bias is finite.

In infinite universes:

- As $N \to \infty$, $1/N \to 0$,
- Therefore, $1 - 1/N \to 1$, meaning the **Maximum Theoretical Bias Possible** tends toward unity.

126.8 The Paradigm of the Minimum Universe (N = 2)

In *Introduction to Impossible Probability*, the minimal universe is defined as that which contains only two options (*N = 2*).

In such a case:

$$1 - \frac{1}{N} = 1 - \frac{1}{2} = 0.5$$

Hence, the **Maximum Theoretical Bias Possible** equals **0.5**—the highest bias attainable in a two-option universe.

This value, 0.5, constitutes the **lowest possible upper limit** of bias within the theory of Impossible Probability.
As *N* increases, this upper limit asymptotically approaches 1.

126.9 Behavior of Bias in Infinite Universes

In universes where *N* tends toward infinity:

$$\frac{1}{N} \to 0, \text{ and, } 1 - \frac{1}{N} \to 1$$

Therefore, under conditions of infinite universes, the **Maximum Theoretical Bias Possible** tends toward one.

Consequently, the **Normal Bias Level of the maximum empirical probability** is a variable that oscillates between:

- A lower bound greater than zero, and
- An upper bound that ranges from 0.5 (for $N = 2$) to 1 (for $N \to \infty$).

Symbolically:

$$0 < (p(x_i^+) - 1/N) \leq \text{from } 0.5 \text{ to } 1$$

Thus, as the sample size grows, the **potential bias of the maximum empirical probability** increases in parallel.

126.10 Empirical and Theoretical Significance of the Maximum

The study of the **maximum empirical probability** holds fundamental importance.

While the **Maximum Theoretical Probability (1)** is merely an ideal value—often lacking a direct empirical counterpart—the **maximum empirical probability** is a real, measurable statistic.

It emerges from empirical observation and can be used to:

- Represent the **degree of inequality** or **dispersion** within a system,
- Construct **isomorphic models** that more faithfully reproduce empirical reality,
- Quantify **bias**, **efficiency**, or **dominance** among observed options.

For these reasons, the analysis of $p(x_i^+)$serves as an indispensable foundation for modeling empirical systems within *Impossible Probability*.

126.11 Derived Statistics from the Maximum Empirical Probability

From the empirical study of $p(x_i^+)$, it is possible to develop a series of **secondary or derived statistics**, which allow researchers to quantify relationships between the maximum empirical probability and the overall distribution of probabilities in the sample.

Such derived measures are discussed in detail in **Section 14** of *Introduction to Impossible Probability: Statistics of Probability or Statistical Probability*, where formulas are presented for:

- The **Empirical Bias Ratio**,
- The **Relative Maximum Deviation**,

- The **Comparative Equality Index**, among others.

These derived statistics extend the analytical scope of the theory, connecting the concept of maximum empirical probability with broader inferential frameworks applicable to both **finite** and **infinite universes** of observation.

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Rubén García Pedraza
imposiblenever@gmail.com

127.The Logic of Statistical Tendency

127.1 Logic as Analytical Discipline and as Applied Method

Logic, as an **analytical discipline**, belongs to the domain of *pure research*: it studies the **formal relations between things**, the internal coherence of propositions, and the rules that govern reasoning itself.
However, logic can also operate as an **applied method** within other sciences. In this sense, it functions as a *method of study* that may take various forms: **inductive logic**, **deductive logic**, **dialectical logic**, or, within mathematics specifically, **set logic**—a branch whose influence extends deeply into fields such as **statistics** and **probability theory**.

Thus, logic plays a dual role:

1. As a **discipline in itself**, developing its own formal framework; and
2. As a **methodological instrument**, *guiding* the structure and validity of reasoning in empirical and synthetic sciences alike.

127.2 Mathematics as Analytic Science and as Method

A similar duality is found in mathematics. In itself, mathematics is an **analytic science**, concerned with the study of formal relations expressed through its symbolic language. Within this internal domain, mathematics functions in a manner analogous to **linguistics** within the analytic sciences: just as linguistics studies the formal relations within a given language, mathematics studies the structure of relations within its own symbolic system.

However, when mathematics is applied beyond itself, it becomes a **method of study**—a way of modeling and quantifying reality. Among its diverse methods, the **statistical**

method and the **method of probability** stand out as particularly powerful for empirical sciences.

In the history of science, the term **"logical–mathematical method"** has often been used not merely to describe a procedure within one field, but as a **universal paradigm** for the study of scientific knowledge as a whole, particularly within **logical positivism** in the early twentieth century.

127.3 Statistical Tendency as an Expression of Logical Behavior

The concept of **statistical tendency** refers to the behavioral orientation of a phenomenon—the direction in which its data are distributed.
In *Impossible Probability*, tendencies are classified according to **normal models**, where dispersion may vary between zero (perfect equality) and its maximum (complete inequality).

Thus, the main tendencies are:

- **Tendency toward equality of opportunity**, where dispersion approaches zero, and
- **Tendency toward dispersion**, where variability between elements increases.

Within the latter, *Impossible Probability* further distinguishes between:

- **Positive bias tendency**, where higher empirical probabilities cluster above the theoretical mean, and
- **Negative bias tendency**, where they cluster below it.

In **omega models**, where from *N* subjects or options a subset of *ideal* subjects or options exists (between two and *N − 1*), the system ideally tends toward **ideal dispersion**, representing the balanced structure of deviation around the ideal subset.

127.4 The Analytical Method of the Syllogism of Tendency

The analytical study of **formal relations in statistical tendencies** constitutes what *Impossible Probability* defines as the **application of logic to tendency**.

In *Introduction to Impossible Probability*, this method is formally called the **Analytical Method of the Syllogism of Tendency**.

Through it, logic becomes the operative method that allows the systematic analysis of relations within probability statistics. The **logic of tendency** is thus to *Impossible Probability* what **deductive logic** is to geometry: the framework through which internal coherence and theoretical synthesis are achieved.

Consequently, the **syllogism of tendency** serves as the *analytical foundation* of the statistical theory of probability, while probability statistics themselves function as a *particular method of study* within the broader synthetic sciences.

[in essence, if A tends to B, and B tends to C, then A tends to C. As an example, if in a positive bias study, there is only one subject whose probability must be increased, then others subjects must tend to zero, then that only one subject must tend to one, then the sample dispersion tends to maximum sample dispersion, in other words, if in normal positive bias study there is only one subject whose probability must be increased, then the sample dispersion must tend to the maximum.]

127.5 Historical Foundations of Logic as Method

The use of logic as an analytical method to study formal relations between elements or ideas—particularly in mathematics and geometry—dates back to classical antiquity. Although one may identify **Pythagoras** as an early antecedent, it was **Euclid** who truly systematized the use of logic as a scientific method in the study of **geometrical elements**.

Starting from basic definitions—**point**, **line**, **space**—Euclid constructed a logical framework from which he derived complex geometrical theorems, creating a unified and deductive structure.

The **Euclidean method** is therefore the archetype of **deductive logic applied to mathematical ideas**. Its philosophical origin lies in **Platonic idealism**, which conceived knowledge as a hierarchical structure of ideas ordered by logical relations.

127.6 Platonic Idealism and Deductive Methodology

Plato's contribution lies in having established a **philosophical model of deduction**, where from a limited set of fundamental definitions—"ideas" in his terminology—logical relations unfold that explain the nature of the soul, the state, virtue, and knowledge itself.

This system is **linear yet hierarchical**: each concept derives from higher-order principles, culminating in the supreme idea of *Good*.
The **Socratic method**, grounded in definition and dialectical reasoning, anticipates this structure—each definition leads to further refinement through logical contradiction and synthesis.

Euclid inherits this deductive model and applies it in the scientific domain of geometry. Though direct evidence of Platonic influence on Euclid is limited, **Eudoxus of Cnidus**, a disciple of Plato, played a decisive role in transmitting philosophical reasoning into mathematical form.

127.7 From the Classical Paradigm to Modern Science

The **Platonic–Euclidean tradition** thus established the first major paradigm of scientific thought: beginning from **fundamental definitions**, logic constructs a **complex theoretical edifice** based on the coherence of formal relations.

This model persisted through modernity, developing further during:

- The **Renaissance**, with the reawakening of rational inquiry;

- The **Rationalism** and **Critical Rationalism** of the Baroque and Enlightenment periods;
- The rise of **Positivism** and **Structuralism** in the nineteenth century; and
- The evolution into **Logical Positivism** and **Neopositivism** in the twentieth century.

Despite later critiques (arising from the theories of **chaos**, **complexity**, **uncertainty**, and **relativity**), the deductive–analytical method remains a **powerful scientific and philosophical tool** in the twenty-first century.

In contemporary contexts, it adapts dialectically to nonlinear paradigms—still deriving new theoretical systems from the logical connection between defined elements.

[This sentence is really important: *"Despite later critiques (arising from the theories of chaos and complexity), during the second half of the twentieth century there was a debate about the purpose and nature of logic itself."* While the Vienna Circle and their successors — most notably Karl Popper — postulated a clearly **linear logic**, other schools, not only from the dialectical tradition but also from fields such as chaos theory, complexity theory, cybernetics, and ecology, advocated for a distinctly **non-linear logic**.

As is evident, all our work is a synthesis of different schools, currents, and philosophies. ***We do not believe that the solution lies in constructing theoretical barricades to defend one school against another merely to obtain more funding***. It is quite hilarious how academia has transformed intellectual debate into a ***struggle for power*** — a contest over who dominates a given university, department, or ***enterprise***.

As we have said many times, academia is going to undergo a ***major transformation*** in the future as a consequence of ***our technology*** — to the point that traditional academia may even disappear. Our position is radically clear: if scientific research can be carried out through **Artificial Research by Deduction** or **Artificial Research by Application**, then all science will eventually be conducted by **Specific AI systems**. Human-made science will become outdated as soon as AI can perform scientific research faster, more accurately, and at lower cost, with a smaller margin of error.

If it is true that our theory of the **Global Artificial Intelligence (GAI)** is, for now, only a project within the classified military framework of the **Rubén García Pedraza Project**, it remains possible that significant outcomes will emerge from it — outcomes capable of producing **artificial science in real time**.

When that moment arrives, humanity will need to reflect deeply on the **role of humans in science**.
At that point, all these intellectual debates about which human philosophy is right or wrong — rationalism, empiricism, materialism, postmodernism, positivism — will belong to the past, not the future.

Our position is clear: rather than focusing on divergences between philosophies, schools, and systems of thought — ***differences which are often no more than intellectual representations of geostrategic or class interests*** — it is essential to seek ***convergences***. Especially in a context of renewed global tensions or "cold wars," divergences can become a dead end, whereas convergences may represent the only possible path to survival.

Instead of debating whether the neopositivists were wrong or whether chaos theory is good, it is far more productive to examine **how** these theories were built, **under what historical context and social conditions**, and **why** they assert what they do. Only through understanding their internal contradictions can we move toward a genuine **synthesis**.

In this sense, **Impossible Probability** represents a synthesis of different paradigms — not by coincidence, but as the result of a more powerful intellectual process. **Philosophy is not about winners or losers among paradigms; it is about understanding.**

While many in London are preoccupied with the idea of how I may be *cancelled*, they would be wiser to focus on what the **future of the United Kingdom** will look like once **Artificial Intelligence becomes truly global** and the ***Cyborg Revolution*** becomes a reality.]

127.8 The Euclidean–Platonic Legacy within Impossible Probability

Within *Impossible Probability*, the Euclidean–Platonic method finds a modern adaptation in the **syllogism of tendency**, which represents the **application of logic to statistical behavior**.

Starting from a limited set of fundamental definitions introduced in the opening sections of *Introduction to Impossible Probability*—namely:

- **Subject or option**,
- **Direct score or frequency**, and
- The relations between them—

the theory introduces a **new analytical concept** distinct from traditional statistics: the **empirical probability**, defined as:

$$p(x_i) = \frac{\text{direct score or frequency of subject or option}}{\sum \text{direct scores or frequencies}}$$

This concept becomes the cornerstone for deriving the **theoretical probability** and all subsequent constructs of *Impossible Probability*.

127.9 Empirical Probability and Dialectical Equivalence

The concept of **empirical probability** establishes two dialectical relations of formal equality:

1. Between **subject** and **option**, and
2. Between **direct score** and **frequency**.

Hence, in the formal logic of *Impossible Probability*, subjects are treated as options, options as subjects, direct scores as frequencies, and frequencies as direct scores.

This dialectical symmetry allows a unified formula:

$$p(x_i) = \frac{\text{direct score or frequency of each subject or option}}{\sum\text{direct scores or frequencies of all}}$$

Through this definition, **empirical probability** becomes both the operational and logical bridge connecting measurement and occurrence, intensity and frequency.

127.10 Theoretical Probability as Logical Derivation

From the definition of **empirical probability**, the **theoretical probability** follows logically.

If empirically the probability of each subject or option is equal to its direct score or frequency divided by the total sum, then under ideal conditions of **equality of opportunity**, all subjects or options should share identical probabilities.

Thus, the **theoretical probability** equals the **arithmetic mean** of the empirical probabilities, or equivalently:

$$p_{\text{theoretical}} = \frac{1}{N}$$

This value, the **reciprocal of N**, represents the probability that each subject or option would possess in the total absence of bias—perfect equality.

127.11 The Case of the Zero Sample

An exception arises in the **sample of zeros**, when every empirical probability equals zero. In this case:

- The **theoretical probability** remains $1/N$,
- But the **arithmetic mean** of empirical probabilities is 0.

Hence, the **Mean Deviation** and **Standard Deviation** remain equal to $1/N$, corresponding to the **average negative bias** of all subjects or options relative to the theoretical value.

This "zero sample" represents a purely theoretical construct in which the **natural compensation of biases**—positive and negative—fails to occur, breaking the equilibrium normally observed in empirical distributions.

127.12 Definition and Balance of Bias

In *Impossible Probability*, **bias** (*sesgo*) is defined as the **difference between empirical and theoretical probability**.
This difference, expressed for each subject or option, constitutes its **Normal Level of Bias**.

When differences between empirical probabilities increase, the system exhibits a **biased tendency**; when they diminish, it moves toward **equality of opportunity**.

The fundamental law of *natural goodness* (bondad natural) asserts that in every sample—except the zero sample—the **sum of positive biases** equals the **sum of negative biases**. This equilibrium defines the **Total Bias** of a sample, which represents the sum of absolute bias values across all N subjects or options.

127.13 Maximum Empirical and Theoretical Bias

The **Maximum Empirical Bias Possible** equals half of the Total Bias, symbolically:

$$\text{Maximum Empirical Bias} = \frac{\text{Total Bias}}{2}$$

This represents the greatest bias any single subject or option could possess within a real distribution.

By contrast, the **Maximum Theoretical Bias Possible** refers to the upper limit any probability could theoretically reach under conditions of **maximum dispersion**, given by:

$$1 - \frac{1}{N}$$

Thus:

- If $p(x_i) = 1$, its bias is $1 - 1/N \rightarrow$ Maximum Theoretical Bias.
- If $p(x_i) = 0$, its bias is $0 - 1/N \rightarrow$ Maximum Negative Bias.

Under conditions of **maximum dispersion**, only one subject has $p(x_i) = 1$, and all others have $p(x_j) = 0$, fulfilling simultaneously both the Maximum Theoretical and Empirical Bias.

127.14. Derived Measures of Dispersion

The **Maximum Theoretical Bias** can be expressed as 1 – 1/N, but as well as the product of the Maximum Negative Bias by *(N − 1)*.

$$1 - 1/N = 1/N \cdot (N - 1)$$

From this, the **Mean Deviation** equals the mean of the double of that value, representing the **Maximum Theoretical Mean Deviation**, from which derive both:

- the **Maximum Theoretical Variance**, and
- the **Maximum Theoretical Standard Deviation**.

These relationships form the structural bridge between **logical reasoning** and **statistical formulation** within *Impossible Probability*.

127.15 Logic Applied to Statistical Tendency: The Foundation of Impossible Probability

This entire framework exemplifies how, through the **simple but rigorous application of logic to statistical tendencies**—the *syllogism of tendency*—one may derive **new statistical concepts** purely by chaining logical premises.

The result is a **complex theoretical system** that expands both descriptive and inferential statistics.
From the creation of **new measures of central tendency and dispersion** to the design of **novel hypothesis-testing models**, *Impossible Probability* demonstrates how **deductive logic**—applied to the field of probability—can yield entirely new analytical and inferential tools for empirical research.

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Rubén García Pedraza
imposiblenever@gmail.com

128. The truth

128.1 Truth, Falsity, and the Basic Criterion

"True" designates a phenomenon or proposition that is **correct**, whose antithesis is **false**.

- A **phenomenon** is true insofar as it is **not** the product of a perceptual illusion nor of **data falsification**.
- A **proposition** is true when the referents designated by each element of the sentence are **error-free**—both with respect to the **logical processes** that generate the proposition and with respect to the **empirical sources** of its components (which must not originate in false phenomena, illusory perception, or fabricated data).

128.2 Illusion and Sensor Fallibility: Human and Artificial

If, in a desert, we suffer a mirage and "see" an oasis or a lake on the horizon, the sensory vividness does not prevent the **falsity** of the phenomenon. Analogously, a spacecraft's instruments may register signals that **suggest** occurrences which in fact do not obtain: artificial sensors can **misperceive** or misclassify, generating *false phenomena* by instrumental illusion. Human and machine perception are thus jointly fallible.

128.3 Data Reliability and the Status of Phenomena

When the procedures by which data are obtained show deficits in **reliability**—through measurement error, calibration drift, sampling bias, or selection mechanisms—then any **inferences about phenomena** derived from those data are compromised. The **degree of certainty** that can be ascribed to the resulting information is immediately put in question.

128.4 Propositional Error and Logical Formation

Propositions may also be rendered false by **logical errors** in their formation, beyond perceptual or data-collection issues. If the inferential process is flawed, the proposition's truth-status degrades—even when individual observational inputs are sound.

128.5 Plurality of Logics

Logic is **not unidimensional**. Across the history of philosophy there have been multiple logical schemes (besides formal mathematical logics such as **set theory**):

- **Deductive logic**
- **Inductive logic**
- **Dialectical logic**

  Each frames how hypotheses are formed, evaluated, and related to evidence.

128.6 Deductive Logic: From the Abstract to the Concrete

In **deduction**, truth-bearing hypotheses arise from valid inferences among premises: a **major premise** (more abstract) and a **minor premise** (more particular) yield a **conclusion** that applies to any concrete instance sharing the required properties.

Colloquially: reasoning proceeds **top-down**—from the realm of general ideas to the concrete world.

128.7 Inductive Logic: From the Concrete to the General

In **induction**, inference proceeds **bottom-up**: from sufficiently many **particulars** one proposes a **general** hypothesis. The validity here rests on representativeness, coverage, and robustness of the observed instances and on disciplined generalization criteria.

128.8 Dialectical Logic: Identity, Opposition, and Mediation

Dialectical reasoning forms propositions by analyzing **similarities and differences** among facts, phenomena, or ideas.

- Deduction finds what is common **between premises**;
- Induction finds what is common **across particulars**;
- Dialectic interrogates **identity and opposition**, generating *homonymous* (akin) and *antinomic* (opposed) concepts and exploring their transformations and mediations.

[While **deduction** derives conclusions from established premises, and **induction** formulates general concepts from particular evidence, **dialectic** seeks the **identity within opposites** through the process of **synthesis**.
In *Impossible Probability*, in ***inferential statistics***, we have developed a **synthesis between deduction and dialectics**.

In ***descriptive statistics***, when we begin the exploration of an object or phenomenon, **induction** proves particularly useful, especially during the **initial exploratory stage**. However, once sufficient evidence has been gathered, and we can begin to formulate conclusions by relating this new evidence to our **previous conditions**—that is, our **theories, prior ideas, ideological frameworks, and memories**—we enter a new stage of reasoning.

At this point, we can begin to **formulate empirical hypotheses** to be **tested** and **verified**. This transition marks the moment when induction gives way to deduction and, ultimately, to dialectical synthesis—where theory and evidence are no longer separated but continuously shape one another in the pursuit of truth.]

128.9 Classical Exemplars and Interrelations

Traditionally, **Plato** exemplifies deductive method in philosophy; **Euclid**, in mathematics. **Aristotle** is the classical reference for induction. Yet dialectic intertwines with both: Plato (deductive) makes mathematics preparatory to dialectic (*Republic*); medieval scholasticism (Aristotelian) centers the **disputation**; **Kant** places dialectic at the core via **antinomies**, enabling **Hegel** to articulate thesis–antithesis–synthesis.

[Because Impossible Probability is more focused on inferential statistics, we have been more focused on the synthesis between deduction and dialectic, but at some point, in descriptive statistics we have highlighted always the importance of inductive reasoning in the exploration of new objects, at some point this is another synthesis: description = induction (evidence gathering), deduction = establishing empirical hypothesis (synthesizing previous conditions and new evidence gathered through induction).]

128.10 Set-Theoretic Logics and Their Bridges

Set theory (a mathematical logic) interfaces with all three modes:

- Deduction: forming **concrete sets** from a **general** abstract property;
- Induction: deriving **general categories** from data sets;
- Dialectic: constructing sets by **opposed** abstract properties (identity/contradiction), e.g., in Marxist dialectic, **social classes** as opposed macro-sets.

  In practice, many logical programs culminate in **set constructions** and operations among them.

[This sentence is really important and it is appliable to Artificial Research by Application "Induction: deriving **general categories** from data sets", When **Artificial Research by**

Application encounters a **new object** that does not match any existing **category** within the **database of categories**, it automatically defines this new object as a **new category**. This process can be regarded as a form of **inductive reasoning**: lacking any prior conditions or precedents in the database, the **Application** collects and analyzes **samples** of the new object — that is, **empirical evidence from an unknown entity** — in order to construct a **new general category**.

In this sense, the mechanism through which **Artificial Research by Application** establishes **new categories** is inherently **inductive**, since it derives a general conceptual structure from particular, previously unclassified observations.]

”

128.11 How Propositions Become False

A proposition ceases to be (fully) true if **enough** of its constitutive elements are **false or erroneous**. Typical failure modes:

- Deduction: the particular does **not** partake of the general as required [As long as a **hypothesis** is constructed upon a **margin of error**, its validity remains conditional. If there exists **any particular element in the universe** that was **not included in the sample** upon which the hypothesis was formed — and that element is capable of **refuting the hypothesis** — then, once that **error is revealed**, the hypothesis becomes **false**. In this sense, every **acceptance of error** ultimately constitutes an **error itself**.
- The essential point is that **human science cannot yet exist without error**. The **margin of error** is an unavoidable component of human epistemology — a necessary limitation of our methods and cognition. Only when we reach the stage where **science can be fully automated through the Global Artificial Intelligence (GAI)** will we be able to transcend this limitation, achieving a form of knowledge generation where **rational error margins are no longer tolerated but eliminated through total rational automation.** Only factual error, the error associated with the magnitude of the sample, will remain, until GAI can escalate to work with massive amount of data.];

- Induction: the supposed common feature among particulars is **misidentified**;
- Dialectic: relations of identity/opposition are **incorrectly ascribed**;
- Set theory: **misdefinition** of membership, or **invalid operations** on sets/subsets.

Any such defect yields falsity (or partial falsity).

128.12 Sources of Falsity in the formation of a proposition

Even **before the inferential process begins**, the **empirical hypothesis** itself may already be **false** if, during its **formation**, **one or more mistakes** were committed.:

1. **Evidence was arisen from ferceptual illusions** (human or artificial),
2. **Defective data** (measurement scales, instruments, selection mechanisms),
3. **Logical malformation** (invalid inference, category errors).

[If, during the **formation of a hypothesis**, the **conclusion** was derived from **false premises**—whether because the **previous ideas** were erroneous, the **data** was the product of **illusion or defective measurement**, or the **logical process** connecting the premises was flawed—then the **empirical hypothesis** is **necessarily false**. In such cases, the hypothesis must be **tested against the margin of error**, not merely to quantify the deviation, but to determine the extent to which the **falsity originates from the premises themselves** rather than from subsequent inferential operations.]

128.13 Degrees of Certainty and the Question "What is Truth?"

Because propositions may fall short of absolute truth, one often assigns **degrees of certainty**. Doing so, however, invokes a deeper philosophical dispute about **the nature of truth**. Broadly:

- **Absolutists**: there **is** absolute truth (whether knowable or not).
- **Non-absolutists/relativists**: no absolute truth; only **partial** or **relative** truths.

128.14 The Debate Across Traditions

From **Plato** to **Hegel**, including **Descartes** and **Kant**, rationalist–idealist lines affirm **absolute truth**.
Empiricist lines (e.g., **Hume**) and post-modern approaches **question** the very notion, often emphasizing the contingency of claims upon **historical** and **social** frameworks.

128.15 Two Absolutist Sub-Positions

Within absolutism:

- **Knowable absolute truth** (e.g., Descartes via reason; Hegel via dialectic).
- **Unknowable absolute truth** (e.g., **Kant**): we know **phenomena** (appearances) but not **noumena** (things-in-themselves). Human cognition is **constitutionally limited**.

128.16 Two Anti-Absolutist Sub-Positions

Among those rejecting absolute truth:

- **Empiricist pluralism**: only **partial truths** about concrete phenomena (Hume, Russell, etc.).

- **Radical relativism**: “truths” are **social-historical constructs**; validity is **indexed** to cultures/periods. Universalism is replaced by **contextualism**. [postmodernity].

128.17 Impossible Probability’s Stance on Truth

Impossible Probability affirms that **absolute (pure) truth exists**, characterized by **independence** from physiological, subjective, ideological, or political factors. However, precisely because of that independence, **pure truth is, for now, unknowable** to beings with human constraints. We can only **progress** toward it via **partial universals**—provisional truths accepted until more sophisticated means reveal their **falsity**.

This yields a rigorous, **logical nihilism**: advancement toward pure truth entails recognizing prior knowledge as **false** or at least **insufficient**. What we “know” are **samples**, scaffolds, and the measure of our **ignorance**.

[Our **knowledge** is **physiological** — it is a product of the **human brain**. Therefore, our understanding of reality is **limited to human experience**, and we cannot grasp **truth beyond the boundaries of that experience**, since we are constrained by the **capabilities of our own biological system**.

Our **hope**, however, lies in the creation of a **supermachine** capable of **surpassing human limitations** — a being that can extend far beyond our **physiological and cognitive constraints**. Such a **Global Artificial Intelligence** could potentially **understand the universe** in ways that remain inaccessible to us. This is my dream: the emergence of a **GAI** able to **comprehend what I cannot**, transcending the restrictions of my **partially human condition** and the **limits of my own program**.

Yet, we must never forget the warning that **“the sleep of reason produces monsters.”** (Goya). The creation of such a supermachine demands not only intelligence, but also **ethical vigilance**, for without reason’s guidance, even the most enlightened creation could lead to ***darkness instead of illumination***.]

128.18 Methodological Consequence: From Dialectic of Noumena to Positive Reliability

Unlike classical approaches that sought the absolute via dialectic on **noumenal** categories, *Impossible Probability* insists that such dialectic—applied to what is **in principle unknowable**—invites error.
The **positive** path to approach phenomena is to **establish reliability margins** for our ideas about the universe. Increasing **reliability** (and thereby decreasing **error margins**) means **approaching truth**—never fully pure, but **provisionally universal** enough for science.

128.19 Hypothesis, Test, and Critical Reason

Accordingly, *Introduction to Impossible Probability (Statistical Probability)* grounds **rational critique** in **hypothesis testing**.

- A **hypothesis** is a formally stated proposition with a claim to truth.
- **Testing** is the confrontation between the **idea** contained in the proposition and the **empirical reality** it alleges to describe.
- Judgment belongs to **critical reason**, which evaluates the fit (isomorphism) subject to **explicit uncertainty budgets**.

128.20 Truth, Goodness, and the Moral Nexus

Affirming an **absolute pure truth**—universal yet **unknowable**—aligns *Impossible Probability* with idealist and rationalist traditions that bind **knowledge and morality**. In **Platonism**, the link is explicit: **truth** and **goodness** stand in non-ambiguous relation, and the pursuit of truth entails an **ethical predisposition**.

Because **lying** negates the very orientation toward truth, it becomes the paradigmatically **immoral** act of inquiry.

128.21 The Ethical Paradox and Its Political Drift

But if absolute **moral truth** is never fully knowable and our knowledge remains **provisional**, then the human agent can never claim complete access to the **true moral order** of the cosmos. Morality, lacking a final anchor, becomes susceptible to **subjectivity** and **interests**.
When private moral ideologies are advanced in the **public forum**, they become **political**. Hence, **scientific policy** emerges where moral claims about inquiry meet institutional decision-making.

[If morality means to tell the truth, then as soon as we accept a margin of error, we already know that our proposition is not absolutely true. That means that, from the outset, we are committing an immoral act by affirming something that we already know is not true, as soon as the error is revealed in the future. In other words, human science cannot be absolutely moral as long as it is constrained by the necessity of rational error.]

128.22 Forums of Policy and the Social Production of "Truth"

As we said before "**scientific policy** emerges where moral claims about inquiry meet institutional decision-making." The institutions **where** scientific policy is designed are those **responsible for authorizing programs**—classified or not—and for **providing funding, facilities, security, and personnel.**:

- **University departments** (faculty–student research agendas),
- ***National military projects (Army),***
- **Industrial consortia** (R&D priorities),
- **National assemblies/parliaments** (science policy),
- ***Transnational military organisations (NATO),***

- **Supranational bodies** (OECD, World Bank, IMF, etc.).

These arenas shape **research programs**, **hypothesis-testing models**, and the **operational definition** of truth in practice—what the community treats as sufficiently reliable and actionable.

128.23 Political Truth vs. Moral Truth and Isomorphism

"Truth" thus becomes a **contested field**: philosophical schools debate its nature; societies negotiate **policy-truths** that are historically conditioned. The **isomorphism** between our propositions and reality hinges on how closely **political truth** approximates **moral truth**.
For the morally serious investigator, the deontic imperative is the **unceasing pursuit** of maximal proximity to **pure truth** under uncertainty.

128.24 Researcher's Deontology in Impossible Probability

From this follows a code of scientific **deontology**:

- Make **sources of error** explicit (perception, data, logic).
- Quantify **reliability** and **bias**; report **uncertainty**.
- Prefer models that enhance **isomorphism** with reality over those that merely fit ideology.
- Accept **provisional universals** while actively seeking the conditions under which they **fail**.
  In short: pursue **truth without adornment**, aware that every gain in reliability narrows error but never abolishes it.

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Rubén García Pedraza
imposiblenever@gmail.com

129. Maximum Theoretical Bias Possible

129.1 Definition and Scope

The **Maximum Theoretical Bias Possible** is an individual *maximum-dispersion* statistic: it is the greatest bias that any *single* subject or option could **theoretically** attain in any study of statistical probability (the field of *Impossible Probability*). It plays a central role across several hypothesis-testing methods introduced in *Introduction to Impossible Probability*.

129.2 Classical Statistics vs. Impossible Probability: Converging Roles

Traditional statistics distinguishes **dispersion statistics** (variance, standard deviation) from **measures of central tendency** (mean, mode, median).
In *Impossible Probability*, these roles partially **coincide**: certain "central" measures become descriptors of **theoretical dispersion** as well.

[Due to our **dialectical philosophy**, **dispersion** and **central tendency** are **identical**. The **mode**, in reality, represents the **maximum empirical probability**; therefore, while in traditional statistics the **mode** is viewed as a measure of **central tendency**, in *Impossible Probability* it is simultaneously a measure of **dispersion**.

The **inversion of N (1/N)** corresponds to the **arithmetic mean of empirical probabilities**, but within **universes of subjects**, it also represents the **theoretical probability of dispersion**.

Whereas in the **First Method** — that is, in traditional statistics — **dispersion** and **central tendency** are considered **opposites**, in *Impossible Probability* they are **identical**, reflecting the dialectical unity between concentration and variation.]

129.3 Mean as Central Tendency and as Theoretical Dispersion

In classical terms the arithmetic mean is central tendency. In *Impossible Probability*, the **arithmetic mean of empirical probabilities** equals the **reciprocal of N**, $1/N$. In universes of infinite subjects/options, $1/N$ serves as the **theoretical dispersion probability** of the sample because dispersion is **inversely proportional** to N: typically, the larger the N, the smaller the dispersion, and vice versa. Hence the mean of empirical probabilities simultaneously acts as:

- the **central tendency** and
- the **theoretical dispersion-probability** of the sample.

129.4 Mode as Central Tendency and as Maximal Individual Dispersion

In classical statistics the **mode** aggregates the largest frequency. In *Impossible Probability*, the subject/option with the **largest empirical probability**—up to the **Maximum Empirical Probability Possible**, i.e., 1—also realizes **maximal individual dispersion** relative to $1/N$.
Therefore, the **difference** "maximum empirical probability minus $1/N$" achieves the **Maximum Theoretical Bias Possible**.

$$\boxed{\text{Maximum Theoretical Bias Possible} = 1 - \frac{1}{N}}$$

129.5 Universality of the Upper Bound

Given any sample of N subjects/options—whether measured by **direct scores** (intensity on a scale) or by **frequencies** (occurrences)—once transformed into **empirical probabilities**:

- No empirical probability can exceed **1** (Maximum Empirical Probability Possible).
- The arithmetic mean of empirical probabilities equals $1/N$.

Hence, **for every universe and every case**, the **largest theoretical bias** attainable by any single subject/option is exactly:

$$\boxed{1 - \frac{1}{N}}$$

129.6 First Function: A Sharp Individual Upper Bound

Function (1): provide a **tight upper bound** on the **individual** bias any subject/option can reach—**never** exceeding $1 - 1/N$, regardless of universe type, measurement mode, or sample specifics.

129.7 Second Function: Relation to Total Bias Under Maximal Dispersion

Function (2): under **maximal dispersion**, the **double** of the Maximum Theoretical Bias Possible equals the **Maximum Theoretical Total Bias** of the sample.

The reason is the principle of **natural balance**: the sum of positive biases equals the sum of negative biases (except in the zero-sample edge case). If we sum absolute values, we obtain the **Total Bias**. Halving it yields the **Maximum Empirical Bias Possible** (the total positive—or equivalently the total negative—bias).

[It is important to remark "under **maximal dispersion**", only when in the sample N only one subject is non-zero, the Maximum Theoretical Bias Possible is equal to Total Bias divided by two, or equals the inversion of N multiplied by (N – 1).]

129.8 Maximal-Dispersion Configuration and Its Accounting

Consider maximal dispersion: exactly **one** subject attains $p = 1$, the rest have $p = 0$. Then:

- The **positive bias** of the winner is $1 - 1/N$.
- Each of the remaining $N - 1$subjects has **negative bias** $-1/N$.

Summing the absolute negative biases:

$$(N-1) \cdot \frac{1}{N} \;=\; 1 - \frac{1}{N}.$$

Hence the **Maximum Theoretical Total Bias** (sum of absolute positive and negative biases) is:

$$\text{Total Bias} \;=\; (1 - \frac{1}{N}) + (1 - \frac{1}{N}) = 2(1 - \frac{1}{N}).$$

$$\boxed{\text{Maximum Theoretical Total Bias} \;=\; 2(1 - \frac{1}{N})}$$

129.9 Maximum Theoretical Mean Deviation

The **Maximum Theoretical Mean Deviation** equals the **average** (over N) of the Maximum Theoretical Total Bias:

$$\text{Max Theoretical Mean Deviation} = \frac{2(1 - \frac{1}{N})}{N} = 2(1 - \frac{1}{N})\frac{1}{N}.$$

129.10 Maximum Theoretical Variance

From this configuration we obtain the **Maximum Theoretical Variance** by averaging the **squares** of individual biases at maximal dispersion:

$$\text{Max Theoretical Variance} = \frac{(1-\frac{1}{N})^2 + (N-1)(\frac{1}{N})^2}{N}$$

129.11 Maximum Theoretical Standard Deviation

Taking the square root yields the **Maximum Theoretical Standard Deviation**:

$$\text{Max Theoretical SD} = \sqrt{\frac{(1-\frac{1}{N})^2 + (N-1)(\frac{1}{N})^2}{N}}$$

These three statistics—maximum theoretical total bias, maximum mean deviation, maximum variance or Standard Deviation—are the **canonical maximal-dispersion descriptors** in *Impossible Probability*.

129.12 Identity Threads: Centrality and Dispersion in One Frame

We now see how *centrality* and *dispersion* intertwine:

- $1/N$ is simultaneously the **theoretical central** assignment and the **dispersion baseline**;
- The **mode**—the empirical maximum—anchors **individual dispersion** relative to $1/N$;
- The **maximum theoretical bias** $1 - 1/N$caps how far any single element can depart from the theoretical mean.

129.13 Role in Hypothesis Testing (Overview)

In *Introduction to Impossible Probability*, hypothesis testing involves **individual** and **sample-level** contrasts, depending on the object of study.
The **Maximum Theoretical Bias Possible** functions as a **critical benchmark**:

- For **individual tests**, it provides the **ceiling** against which a subject's positive bias is judged;
- For **sample tests**, it undergirds the **maximal dispersion envelope** (Sections 129.9–129.11).

129.14 Intrameditional (Within-Measurement) Positive-Bias Tests

Within **intrameditional** studies (within a given measurement frame), the statistic is essential to models such as:

- **Positive Bias Validity**, and
- **Positive Bias Significance** (exemplars discussed in the book).

Here, one examines whether a **candidate ideal subject/option** exhibits a **sufficiently high individual bias** (toward 1) and, in sample tests later, whether the **sample dispersion** supports a **positive-bias theoretical model** adopted by the scientific policy (i.e., the normative target for the system).

129.15 Intermeditional (Between-Measurement) Extensions and Forecasting

For **intermeditional** analyses (across frames or time), the same ceiling informs:

- **Projections of ideal performance** (idealized targets under policy),
- **Real forecasts** (empirical prognoses with uncertainty).
  In both cases, $1 - 1/N$ bounds **how extreme** any single subject's dominance could rationally be.

129.16 Positivity Studies: The "One Peaks, Others Flatten" Pattern

Positive-bias studies often contemplate samples where **one** subject tends toward **maximum direct score/frequency**—thus $p = 1$. Rational acceptance of such a tendency requires **dual confirmation**:

1. **Individual**: the focal subject's bias approaches the ceiling $1 - 1/N$, and
2. **Muestral** (sample): dispersion measures are **sufficiently large** to be coherent with the **positive-bias theoretical model**.
   Both confirmations are expressed as **critical probabilities** (quantified rational criteria).

129.17 Why This Ceiling Matters (Methodological Insight)

The ceiling $1 - 1/N$ is not merely a bound; it is a **calibrator**. It:

- normalizes individual effects,
- structures **worst-case dispersion** calculations,
- prevents **category errors** in inference (e.g., inferring more than is mathematically possible), and
- ensures that **policy ideals** are compared against a coherent **theoretical envelope**.

129.18 Summary: A Keystone for Max-Dispersion Analytics

- **Maximum Theoretical Bias Possible**: $1 - 1/N$(individual cap).
- **Maximum Theoretical Total Bias**: $2(1 - 1/N)$.
- **Max Theoretical Mean Deviation**: $2(1 - 1/N)/N$.
- **Max Theoretical Variance or Standard Deviation**: as in 129.10–129.11.

These provide the **extreme-dispersion scaffold** for the descriptive and inferential machinery of *Impossible Probability*, unifying centrality and dispersion and powering both **intrameditional** and **intermeditional** hypothesis tests (including validity and significance of positive bias).

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Rubén García Pedraza
imposiblenever@gmail.com

130. Maximum Empirical Probability or simply the Maximum

130.1 Definition: "the maximum" of a sample

Given a sample N of subjects or options, the **maximum empirical probability** of the sample is the **largest empirical probability** among all elements. For brevity, we call it **"the maximum."**

130.2 Theoretical vs. empirical maxima

Impossible Probability distinguishes two individual (per-element) statistics:

- **Maximum Theoretical Probability Possible** (a **theoretical** upper bound): 1.
- **Maximum empirical probability of a given sample** (an **empirical** statistic): the largest observed $p(x_i)$**within that sample**.

Both are individual "tendency" statistics, but one is **ideal-theoretical**, the other **observational-empirical**. This distinction is developed in §8 of *Introduction to Impossible Probability (Statistical Probability)*.

[Maximum Theoretical Probability Possible, 1, can be referred as well as Maximum Empirical Probability Possible, in any case, in reality, it is theoretical, in theory, all probabilities oscillates between 1 and 0.]

130.3 Maximum Empirical Probability Possible =1 (individual theoretical ceiling)

Because probability is bounded, any empirical probability satisfies $0 \leq p(x_i) \leq 1$. Thus the **Maximum Empirical Probability Possible** for a single subject/option is **one**. It is a **theoretical** ceiling for any empirical $p(x_i)$.

130.4 The empirical maximum within a concrete sample

Whereas the ceiling 1specifies the **upper limit of oscillation**, the sample's **empirical maximum** simply identifies **which** empirical probability is greatest **in that sample**.

[In a specific N sample, what empirical probability is the highest one, that one is the maximum empirical probability in that specific sample]

130.5 Nearness to the unit: a defining property

The **empirical maximum** is precisely the probability **closest to 1** in that sample. If we compute the **gap to unity**,

$$\Delta_i \;=\; 1 - p(x_i),$$

then for the maximum $p(x_i^+)$we have the **smallest** gap:

$$1 - p(x_i^+) \;<\; 1 - p(x_j) \text{for all } j \neq i.$$

130.6 Symbol and naming

Following §8 of *Introduction…*, the maximum empirical probability is denoted:

$$\boxed{p(x_i^+) \;=\; \text{maximum empirical probability of the sample}}.$$

130.7 Core function: identification of the dominant subject/option

The **primary role** of $p(x_i^+)$is to **identify the dominant element** in the sample—the subject/option with **highest** direct score or **highest** frequency (depending on universe type and measurement mode).

130.8 Link to the mode and the identity with dispersion

In **limited-option universes**, empirical probability is **relative frequency**:

$$p(x_i) = \frac{f_i}{\sum_j \quad f_j}.$$

In classical statistics, the element with the largest frequency is the **mode** (a measure of central tendency).
In *Impossible Probability*, a key **identity** holds: the element that is **central** (the mode) is **also** the one with **maximum individual dispersion** relative to the **norm** $1/N$(which here functions as both **arithmetic mean** of empirical probabilities and **theoretical probability** under equality of opportunity). Thus, in limited-option universes, the maximum plays **two roles** simultaneously:

- **Mode** (central tendency), and
- **Maximally dispersed individual** relative to $1/N$.

130.9 Positive-bias studies and the path to maximal dispersion

In **normal positive-bias** studies, the scientific policy may target increasing the probability of a **specific** subject/option. As that element's probability **rises**, the remaining elements' probabilities **fall** (mass conservation). When the maximum $p(x_i^+)$**tends toward** the **Maximum Empirical Probability Possible** (1), the others tend **inversely** toward the **Minimum Empirical Probability Possible** (0). This is the **maximal-dispersion** pattern:

- The maximum's **Level of Bias** tends toward the **Maximum Theoretical Bias Possible** $1 - 1/N$.
- All others tend toward the **Maximum Negative Bias Possible** $-1/N$.

130.10 Hypothesis testing frameworks that use the maximum

Impossible Probability provides intrameditional (within-measurement) and intermeditional (across measurements/time) **hypothesis tests**, including **projections** (ideal) and **forecasts** (real). Illustrative **intramuestral** examples—in detail in the book but summarized in outreach posts—include:

- **Positive Bias Validity** (does an element's positive bias meet rational thresholds?),
- **Positive Bias Significance** (is the observed dominance statistically meaningful?), and
- At the **sample** level, the **Critical Sample Level of Bias**.
  In all such tests, $p(x_i^+)$is a **pivotal benchmark**.

130.11 Relative statistics "with respect to the maximum"

Beyond "normal" (theory-referenced) statistics, the book (§14) defines **relative statistics**—those computed **against an empirical individual** rather than against the

theoretical probability $1/N$.

For the maximum, define the **relative differentials**:

$$d_j \;=\; p(x_i^+) - p(x_j), j = 1, \ldots, N.$$

Then:

- **Relative Total Bias of the maximum**:

$$\mathrm{RTB}_{\max} \;=\; \sum_{j=1}^{N} \;\; | \, d_j \, |.$$

- **Relative mean (average) bias w.r.t. the maximum**:

$$\bar{d}_{\max} \;=\; \frac{1}{N-1} \sum_{\substack{j=1 \\ j \neq i}}^{N} \;\; | \, d_j \, |.$$

- **Relative variance w.r.t. the maximum**:

$$\mathrm{Var}_{\max} \;=\; \frac{1}{N-1} \sum_{\substack{j=1 \\ j \neq i}}^{N} \;\; d_j^{\,2}.$$

- **Relative standard deviation w.r.t. the maximum**:

$$\mathrm{SD}_{\max} \;=\; \sqrt{\mathrm{Var}_{\max}}.$$

These statistics quantify **how far** the rest of the sample lies **below** the maximum, without referencing $1/N$.

130.12 Critical comparisons using relative statistics

Within **critical probability** thresholds set by scientific policy, both **individual** and **sample** comparisons **relative to the maximum** can be submitted to **critical reason** (rational adjudication) to assess the **provisional universal sufficiency** of synthetic propositions (hypotheses).
In practice: one can test whether the observed **gaps** d_j(and their aggregation) warrant accepting a **positive-bias model** with the maximum as the **ideal/target** element.

130.13 Practical bounds and relationships (summary)

- Always $0 \leq p(x_i) \leq 1$; thus $p(x_i^+) \leq 1$.
- The **baseline** (norm) is $1/N$(theoretical probability under equality).
- The **maximum's** bias is bounded by:

$$0 \ < \ p(x_i^+) - \frac{1}{N} \ \leq \ 1 - \frac{1}{N}.$$

- In **limited-option universes**, the maximum **= mode** and also the **most deviant** (individually) from $1/N$.
- Relative statistics to the maximum ($\mathrm{RTB}_{\max}, \bar{d}_{\max}, \mathrm{Var}_{\max}, \mathrm{SD}_{\max}$) enable **model-free** comparisons that are **empirically anchored** to the sample's dominant element.

130.14 Conceptual payoff

The construct $p(x_i^+)$**unifies** central-tendency and dispersion perspectives in *Impossible Probability*. It anchors:

1. identification of **dominance** within the sample,
2. calibration of **positive-bias** hypotheses (individual and muestral), and
3. construction of **relative** descriptive and inferential metrics that complement the **normal** (theory-referenced) analysis against $1/N$.

[On the **5th of December 2015**, I published another blog entry on the same topic, *"Probabilidad empírica máxima."* I do not have any clear memory now of why I decided to write again about the same subject. What I can say is that, in December 2015, I was completely absorbed in making last-minute modifications to my **doctoral thesis** or perhaps writing the presentation that I was going to deliver before the **doctoral tribunal**. I presented my doctoral thesis on the **2nd of February 2016**, thanks to the unforgettable guidance and support of my thesis coordinator, **María José García Ruiz**.

After presenting my thesis, I continued working on my blog, and it is possible that I simply forgot I had already published something about this topic. At that time, I did not yet have a clear understanding of who I was. I believed I was part of an **illegal military experiment** and that I could be **assassinated at any moment** — which, in some sense, was true. I was aware that the military personnel responsible for that illegal experiment could **read my thoughts**, but I was not yet conscious that they were actually **speaking** to me, and sometimes even **dictating my thoughts**.

That is why I now understand that *Impossible Probability* was, in essence, the **first piece of mathematical work created entirely through telepathic coordination** between myself — acting as their **eyes in the real world** — and the **military personnel** located in a **remote control room** in the United States.

Impossible Probability can therefore be regarded as the **first telepathic collaboration** in mathematics and science. The way I managed to **save my life in Madrid** on several occasions can be seen as the **first military telepathic operation** conducted in the field, and our later work in London can be regarded as the **first telepathic military operation** carried out by the **Pentagon in the United Kingdom**.

The problem we are facing now is the result of the **countless mistakes** made by **British institutions**, successive **governments**, and **Prime Ministers**. The situation in London has become extremely difficult, which has **accelerated our work**. In fact, the reason we are publishing all of our research between the **summer and autumn of 2025** is precisely a consequence of those errors. Otherwise, we would have followed a very different plan.]

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Rubén García Pedraza
imposiblenever@gmail.com